# Effect of Real-Time Electricity Pricing on Renewable Generators and System Emissions

by

Jeremiah P. Connolly

A.B., Engineering Sciences, Dartmouth College
B.E., Thayer School of Engineering, Dartmouth College

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Author ..............................................................
Engineering Systems Division
May 18, 2008

Certified by ........................................................
Stephen Connors
Director, Analysis Group for Regional Energy Alternatives
Thesis Supervisor

Accepted by ........................................................
Dava Newman
Professor of Aeronautics and Astronomics and Engineering Systems
Director of the Technology and Policy Program

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## Abstract

Real-time retail pricing (RTP) of electricity, in which the retail price is allowed to vary with very little time delay in response to changes in the marginal cost of generation, offers expected short-run and long-run benefits at the societal level. While the effects of RTP on most market participants have been examined previously, its effects on a) renewable generator revenues and b) power sector emissions are not well understood. This thesis presents a counterfactual model of the New England wholesale power market, including within-hour consumer price response, to analyze revenues under RTP for four renewable test cases and emissions of $CO_2$, $SO_2$, and $NO_x$. Assuming a moderate consumer price-response ($\epsilon = -0.3$), I find that revenues for both wind and solar cases will decrease by about 3%, a smaller loss than that expected by the generation sector as a whole ($\sim$ 6%) or by peak generators ($\sim$ 55%). In the same scenario, RTP is expected to decrease emissions of $CO_2$, $SO_2$, and $NO_x$ by 2-3% in the short-run. These results are qualitatively robust across a range of elasticities and other input parameters.

A discussion of the political barriers to RTP highlights interest group pressure from peak generators and the framing of gains and losses for consumers. These barriers are likely to attract significant policymaker attention in RTP discussions, but the results of my empirical analysis show the need to also consider how RTP may interfere with the ability to achieve other policy objectives, including promoting renewable energy and reducing emissions.

Thesis Supervisor: Stephen Connors
Title: Director, Analysis Group for Regional Energy Alternatives

# Acknowledgments

Many thanks are due to a host of people without whom this research would not have been possible. Stephen Connors, my advisor, provided support and insight throughout the entire project. Steve's guidance was invaluable on issues from finding the right topic down to the details of power system dispatch and plant operation. I was continually impressed by how available Steve made himself for his students, from weekly meetings to detailed reviews of my drafts. He has a knack for looking at complexity and finding the right takeaway, and I hope to take that forward with me.

The development of my interests and skills while working on this research owes much to several other faculty and instructors. David Marks was pivotal in my decision to come to TPP in 2006, helped me find financial support and interesting research, and provided advice throughout my years. John Sterman graciously helped me as I articulated my objectives for this research and beyond. Jonathan Raab taught a fantastic energy policy course which sparked the idea for this research, and Rachel Wellhausen provided some critical advice on an early version of what became Chapters Three and Seven here.

In addition, I learned a great deal from a number of my TPP classmates. In particular, Tarek Rached was extremely generous with his time spent answering database and programming questions, and providing advice on visualization and presentation matters.

Finally, I appreciate the gracious financial support of the MIT-Portugal Program and the Massachusetts Renewable Energy Trust.

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# Chapter 1

# Executive Summary and Introduction

This thesis examines the impact that real-time pricing (RTP) of retail electricity would have on

1. The revenue streams of intermittent, renewable generators, and
2. Emissions of air pollutants from the electricity generation sector.

RTP has been proposed to improve the economic efficiency of the power sector by enabling consumers to respond to price, but the effects that such a policy would have on the competitiveness of renewable generators have not been examined, and the literature on emissions impacts of RTP is sparse (see only [22, 21]). In the following sections I summarize my problem statement, methods, and results, focusing on the empirical study which is the center of this research.

## 1.1 Power Markets and Demand Elasticity

Consumer demand for electricity is supplied in most regions by a heterogeneous mix of generators of different ages, technologies, fuels, and cost structures. The implication of this structure is that the cost of power purchased from generators typically varies significantly throughout the day. Flat retail prices, however, mean that consumers rarely face the true variation in marginal cost of generation and thus consume inefficient quantities based on incorrect price signals. In order to improve the price signals that consumers face, many economists and some consumer interest groups have proposed RTP, under which consumers would pay the marginal cost of generation at the moment of consumption, plus some mark-up for power delivery. The benefits of such a policy are not expected to be distributed evenly, but at a societal level RTP should be welfare-improving.

## 1.2 Intermittent Generator Revenues, Emissions, and Electricity Policy

Some impacts of RTP, though, are not well-understood. First, there is a possibility that RTP will have disproportionate effects on intermittent renewable generators. This arises because the wholesale price of electricity has diurnal and seasonal patterns. If consumers respond to RTP by demanding less power in high-price hours and more in low-price hours (and hence lowering or raising the wholesale price in those hours, respectively), changes in wholesale price will therefore have diurnal and seasonal patterns. Since the availability of solar and wind resources also has diurnal and seasonal patterns, their revenue streams will be disproportionately impacted by RTP if their availability pattern is highly coincident with the price-change pattern. These effects have not previously been studied.

Second, the understanding of how RTP will impact the emissions of air pollutants is not well-developed. In regions with lower marginal than average emissions rates in peak hours, for example where coal provides intermediate generation and gas is used for peak demand, RTP may increase emissions by increasing the utilization of intermediate generators. In other regions, for example where hydropower is used for intermediate generation and oil or gas in used for peak demand, the opposite effect is expected. The direction and magnitude of the short-run emissions effect will therefore depend on the details of the power system in question, including its fuel mix but also how it is dispatched hour-by-hour. Research on this effect has been limited.

Understanding these impacts is important for policymakers because numerous policy interventions already exist to encourage renewable generation or control pollutant emissions. Renewable generators benefit from both federal and state industrial policies, in the form of Production Tax Credits, Renewable Portfolio Standards, and Feed-In Tariffs. Emissions are regulated federally by the Clean Air Act (and potential limits on greenhouse gas emissions which are currently being discussed in the Congress) and at the state level through agreements such as the Regional Greenhouse Gas Initiative. Policymakers must understand how a policy such as RTP will interact synergistically or antagonistically with other regulations if they are to achieve their policy objectives. This research is intended to inform the development of a more holistic and coherent set of electricity policies.

## 1.3 Central Question

In order to examine the impact on renewable generators I pose a retrospective question:

> *1. What would producer revenues, and in particular renewable generator revenues, have been if end-users were charged real-time prices?*

The impact on emissions is investigated similarly. I seek to answer the question:

> *2. How would emissions have changed if end-users were charged real-time prices?*

These questions are answered empirically in Chapters Four, Five, and Six, using the methods summarized in the following section.

These analyses improve our ability to consider a larger question of political economy:

> *3. Given that real-time pricing is a welfare-improving policy, what barriers prevent its implementation?*

In Chapter 7 I draw on my empirical analyses and literature from political science and economics in order to address this question.

## 1.4 Method

In Chapters Four and Five I develop a method for evaluating the counterfactual wholesale market prices under RTP in the New England power market from 2003-2006. The model scope includes only the day-ahead power market, treats producer and system operator behavior as exogenous, and considers only within-hour price response with existing technologies. The data behind the model is publicly available from ISO New England and includes the actual bids submitted to the day-ahead market and observed demand and prices. The simulation is described in detail in Chapter Four and summarized here in Figure 1-1.

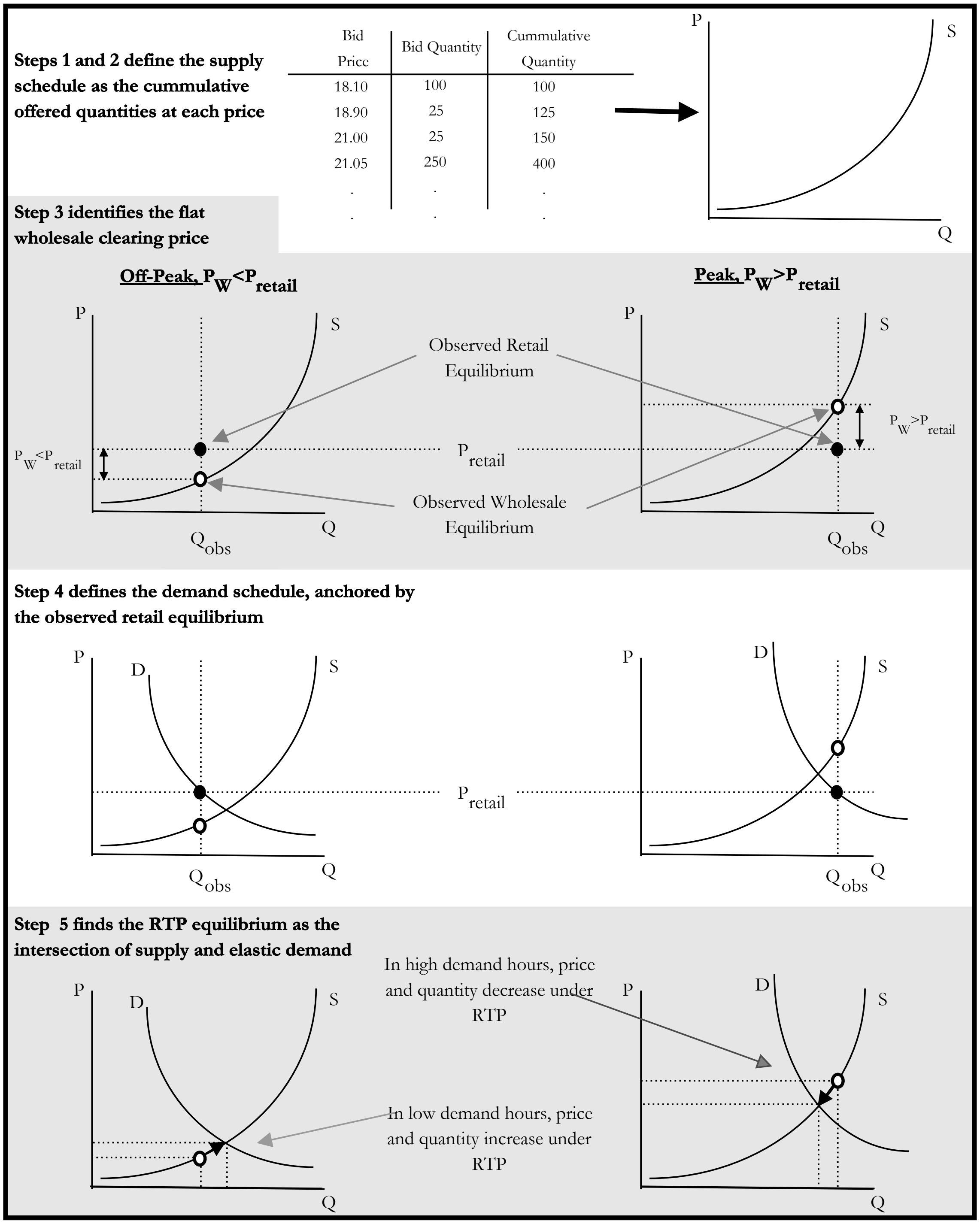
## 1.5 Results

### Renewable Generator Revenues

The results of this simulation support the hypothesis that RTP will affect intermittent generators differently than the generation sector as a whole, but not in the way hypothesized in Chapter Two. Specifically, in the New England power market, intermittent generators may expect revenue losses due to RTP, but these losses will be comparatively less than the losses expected by the generation sector as a whole and much less than the losses faced by peak generators. This result applies to both the solar and wind sites which were considered and holds qualitatively across a number of sensitivity tests, as described in Chapters Four, Five, and Appendix C. For the base RTP scenarios with a moderate elasticity of -0.3, the four intermittent generators considered all face revenue losses of less than 5%, while the average generator expects losses of over 6% and peak generators over 55%. These results are summarized in Figure 1-2 and Table 1.1.

While the basis for this research was revenue, rather than profit, a note should be made that the same revenue loss will have different profit implications for different generation technologies depending on their cost structure. For renewables, hydro, and nuclear, which have close to zero marginal operating cost, a loss of revenue is translated almost entirely to a loss in profit. For coal, oil, and gas, which have significant marginal input costs (primarily fuel but also pollution permits and other costs), a unit loss in revenue may be halved or more when translated to profit loss.

Figure 1-1: Summary: Market Simulation Model



**Steps 1 and 2 define the supply schedule as the cummulative offered quantities at each price**

| Bid Price | Bid Quantity | Cummulative Quantity |
|---|---|---|
| 18.10 | 100 | 100 |
| 18.90 | 25 | 125 |
| 21.00 | 25 | 150 |
| 21.05 | 250 | 400 |
| . | . | . |
| . | . | . |

**Step 3 identifies the flat wholesale clearing price**

**Step 4 defines the demand schedule, anchored by the observed retail equilibrium**

**Step 5 finds the RTP equilibrium as the intersection of supply and elastic demand**

In high demand hours, price and quantity decrease under RTP

In low demand hours, price and quantity increase under RTP

Table 1.1: Summary of Revenue Impacts on Intermittent Generators

| | | %Δ Revenue, RTP Compared to Flat Rate | | |
|---|---|---|---|---|
| Site | Flat Revenue ($) | $\epsilon = -0.1$ | $\epsilon = -0.3$ | $\epsilon = -0.5$ |
| All Generation Sector | 29.02B Gross | -2.5 | -6.3 | -9.2 |
| Hull Near-Shore Wind | 653K/MWi | -1.5 | -3.6 | -5.2 |
| Nantucket Off-Shore Wind | 868K/MWi | -1.4 | -3.6 | -5.2 |
| Northborough *in situ* Solar | 123K/MWi | -1.0 | -2.6 | -3.8 |
| Worcester TMY Solar | 324K/MWi | -1.2 | -2.9 | -4.4 |

*Total revenue shown for generation sector, revenue per MW installed (MWi) shown for renewable sites. Full results and table are presented in Chapter 5.*

## Emissions

The model developed in Chapter Four evaluates hourly changes in quantity in addition to price. Using these changes, in Chapter Six I evaluate the counterfactual changes in emissions of $CO_2$, $SO_2$, and $NO_x$ which would have resulted from an RTP policy from 2003-2006. These changes are evaluated by multiplying the vector of hourly quantity changes by a vector of marginal emission rates of each pollutant. Hourly marginal emission rates were developed for the New England power market using EPA Continuous Emissions Monitoring data and a method which identifies those units that are responding to changes in load in any particular hour and calculates marginal rates as the average of all load-responsive emission rates. This method is documented in Chapter Six and, more thoroughly, elsewhere[14].

The results of this analysis support the hypothesis that RTP would cause small short-run reductions in emissions. Summing across the model period, with the moderate elasticity of -0.3, I find decreases of 2.4%, 1.6%, and 2.9% for $CO_2$, $SO_2$, and $NO_x$, respectively. These results, which are summarized in Table 1.2 and Figure 1-3, are consistent with previous work on short-run emissions and RTP [22, 21]. Long-run emissions impacts are less certain, however. In Chapter Six I speculate that, without regulatory changes, RTP may shift long-run marginal emission rates downwards, based on a comparison of the current marginal and average rates calculated from CEM data. This downward shift may actually impose private costs on future renewable generation investors, since the emissions savings they take credit for will decrease. The long-run effect of RTP on emissions, though, has not been studied in a rigorous way.

Table 1.2: Retrospective Emissions Changes from RTP, as a Percentage Change from Flat Emissions

| Panel A: $CO_2$ | Four-Year Total |
|---|---|
| Flat ($10^9$ kg) | 172 |
| $\epsilon$ = -0.1 | -0.9 |
| $\epsilon$ = -0.3 | -2.4 |
| $\epsilon$ = -0.5 | -3.6 |
| **Panel B: $SO_2$** | **Four-Year Total** |
| Flat ($10^6$ kg) | 461 |
| $\epsilon$ = -0.1 | -0.6 |
| $\epsilon$ = -0.3 | -1.6 |
| $\epsilon$ = -0.5 | -2.5 |
| **Panel C: $NO_x$** | **Four-Year Total** |
| Flat ($10^6$ kg) | 141 |
| $\epsilon$ = -0.1 | -1.1 |
| $\epsilon$ = -0.3 | -2.9 |
| $\epsilon$ = -0.5 | -4.3 |

## Political Economy

In Chapter Seven I combine these economic and environmental results with a more general set of theories of behavior and political processes to explore how various participants in the policy discussion may come to support or oppose RTP policies.

I propose that consumers are unlikely to dedicate significant resources to supporting RTP even though they stand, on average, to gain. At the individual level, prospect theory suggests that, while RTP's net monetary benefits summed for all consumers are positive, the net utility benefits may be negative due to framing effects and the greater affect of losses relative to gains. In other words, the minority of consumers who lose from RTP are expected to be more motivated than the majority of consumers who gain. At the organizational level, consumers face a collective action dilemma – since all consumers may benefit from RTP regardless of whether they devote resources to support it, none would be expected to devote any resources to supporting RTP[1].

Producers, on the other hand, constitute a concentrated interest group which is likely to dedicate significant resources to oppose RTP. Ownership of generation assets in New England does not seem sufficiently segregated by class to create significant conflicts within the producer interest group. A policy of Hicksian compensation could in theory compensate any existing producers for their losses – in effect giving away any short-run benefits of RTP in order to secure the greater long-run benefits of more efficient investment signals. To be successful, such a policy would have to ensure confidence among producers in the government's ability to make long-term commitments (as generation assets may exist 40+ years), but a precedent for such compensatory payments has already been established in the form of stranded-cost payments in the restructuring process. This analysis helps explain why RTP, a welfare-improving policy, has not yet been implemented. To overcome these barriers will require at least a reframing of RTP for consumers, and probably a reliable commitment by the government to compensate producers who lose under RTP.

## Relevance for Policymakers and Investors

The intended audience for this research consists of practitioners in the electricity policy and investment spheres. For these stakeholders, the most relevant results can be summarized as follows:

- In practice, RTP is not a technology-neutral policy. I have shown conclusively that RTP has differential revenue implications for different generation technologies. These revenue impacts, though, translate into inconclusive profit impacts, since some generators have a much higher fraction of fixed costs than others. For policymakers, this result highlights the need to craft coherent and systemic electricity policy, so that policies explicitly aimed at promoting one technology (for example, the Renewable Portfolio Standard) are not undermined by others (which may be the case with RTP). For investors, this research demonstrates a method of forecasting the effects that RTP adoption would have on potential investments.

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[1] Of course, consumers with other-regarding preferences may incur private costs to benefit others, but this possibility is not usually discussed in the classic collective action dilemma.

- RTP is not an emissions-neutral policy. In the New England power market, RTP is expected to reduce short-run emissions but has undetermined effects long-run emissions. The extent to which this increase counters other regulatory objectives should be considered in policy development.

## 1.6 Contribution

The primary contribution of this work is the examination of how renewable generators are impacted by RTP. This effect has not been studied elsewhere, and the results of this analysis should be useful in communicating the fact that electricity pricing policy is not technology-neutral. The model developed in Chapter Four also represents a novel use of observed bid information to simulate counterfactual short-run electricity prices – previous models rely on inference of electricity price from the observed input costs [21]. While each approach may have its own merits[2], this thesis shows at the least a proof of concept of an alternative approach with some advantages. The analysis of emissions in Chapter Six adds to a sparse literature and takes advantage of a novel, and likely superior, method of estimating marginal emission rates which has not yet been incorporated into studies of RTP or, more generally, demand response. Finally, the discussion in Chapter Seven interprets the likelihood of support for RTP using more general theories of behavior and political processes which, to my knowledge, have not been incorporated into previous discussions of RTP support.

## 1.7 Document Outline

The next chapter describes the power market in more detail, with particular focus on the design of the restructured New England power market, and develops the questions which are examined throughout the thesis. Chapter Three surveys the existing literature on RTP, which suggests that RTP is a welfare-improving policy, long-run gains are greater than short-run gains, gains increase with greater elasticity, and the impacts on emissions vary by region. In Chapter Four I develop a simulation model of electricity prices with elastic demand. In

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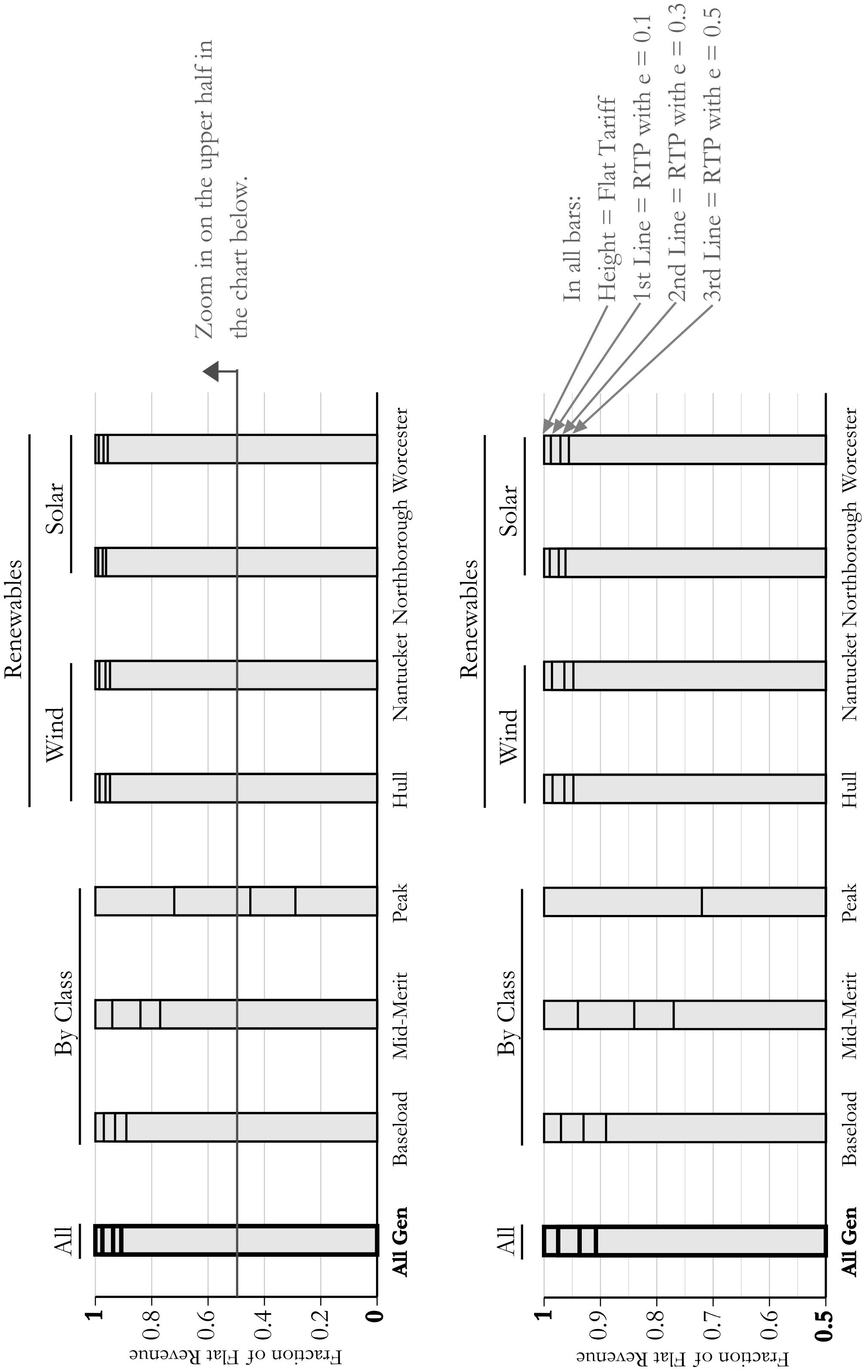
[2] Most prominently, the two approaches differ in their treatment of market power.

Chapter Five I use this model to examine RTP's effects on renewable generators and in Chapter Six to examine RTP's effect on pollutant emissions. Chapter Seven incorporates these findings into a broader discussion of the political economy of RTP, drawing on theories of individual behavior and political processes. Chapter Eight concludes.

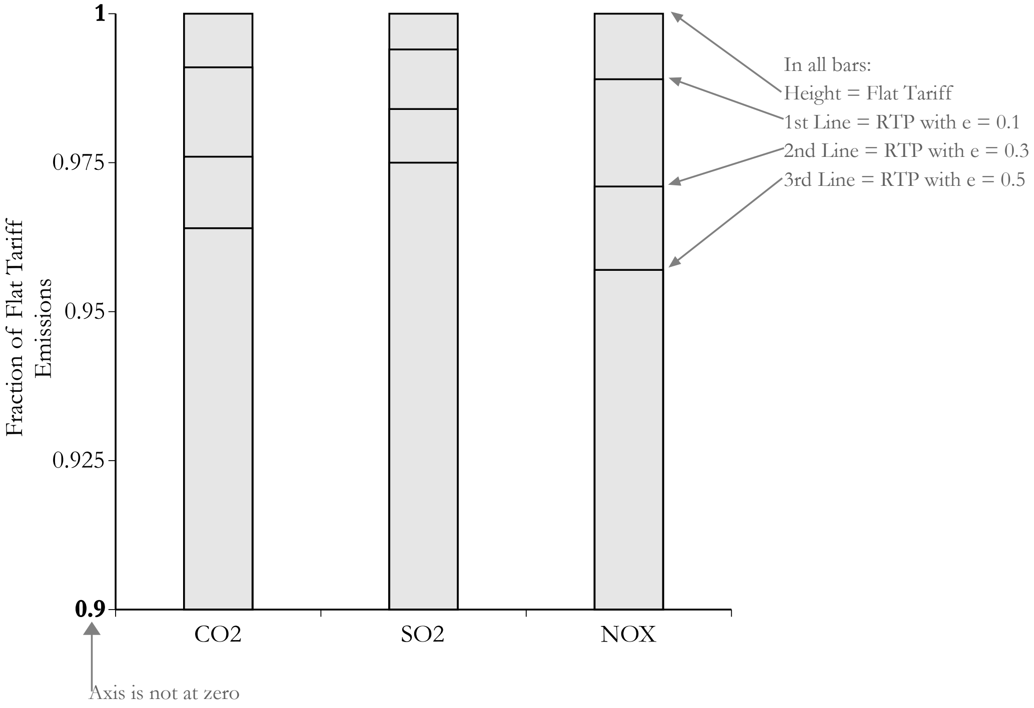
Figure 1-2: Summary: Changes in Annual Revenue Due to RTP



Zoom in on the upper half in the chart below.

In all bars:
Height = Flat Tariff
1st Line = RTP with e = 0.1
2nd Line = RTP with e = 0.3
3rd Line = RTP with e = 0.5

Figure 1-3: Summary: Change in Emissions Due to RTP



# Chapter 2

# The Restructured New England Power Market and Real-Time Pricing

## 2.1 The New England Power Market

This chapter provides a brief description of the system which will be analyzed throughout this thesis. That system is the New England power market, a collection of regulated and semi-regulated submarkets for a variety of products and services that together deliver reliable electricity to end users. The largest pieces of the market involve the sales of two classes of products — a commodity (electricity) and transportation of that commodity (maintaining the quality and reliability of power while moving it over wires). The transportation service is typically referred to as Transmission and Distribution (T&D). In addition, there are markets which ensure reliability through the sales of ancillary services and forward capacity. Before the 1990's, both these functions were performed by vertically-integrated monopolies under regulation by federal and state powers. Regulatory changes from the 1970's to the 1990's eventually gave states the option to restructure their power markets and force the break-up of these vertically-integrated companies[1]. The restructuring that followed in New England created the system which is studied in this thesis.

In the following sections of this chapter, I describe this system and some of the implications of its design. The model developed in later chapters will focus exclusively on the

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[1] Detailed historical accounts of restructuring can be found elsewhere. For example, see Joskow 2000 [24].

commodity market and ignore capacity, reliability, and T&D, so in this chapter I will not discuss markets for transmission in detail. The electricity supply chain is typically thought of in four sectors from raw fuel input to delivered power — generation, transmission, distribution, and retail. The policies I investigate in this thesis directly effect only two transactions — between retailers and end-users and between generators and transmission companies[2]. As a consequence, in the following sections I focus primarily on the submarkets at these two interfaces.

The following sections describe the market in the structure-architecture-rules framework, which is used elsewhere to describe regulated industrial systems [40]. The implications of the market's design, including the need to invest in peak capacity which is rarely used, lead to the proposition that demand-side price response is a sensible policy to consider in the New England power market.

## 2.2 Market Structure and Architecture

*Structure* in this framework refers to "properties of the market closely tied to technology and ownership"[40]. Both aspects of the New England market have changed significantly with restructuring in the 1990's, as generation ownership has shifted and new generation capacity (especially natural gas) has been brought online. The generation sector is now much less concentrated than before restructuring. An October 2007 report lists 86 different entities as primary owners of one or more of the  580 generation units in New England [16]. The five-firm concentration of 45% and Herfindahl-Hirschman Index (HHI) of 661[3] indicate significant disaggregation for an industry with such large economies of scale. Fuel types include coal, natural gas, oil, nuclear, hydro, and some renewables, and generation technologies include steam-, gas-, simple-cycle- and combined-cycle-turbines, hydro, wind, and diesel generators.

*Architecture* refers to "a map of [a market's] component submarkets [including] the type of each market and the linkages between them"[40]. Even ignoring markets for transmission rights, the New England power market consists of perhaps dozens of individual submar-

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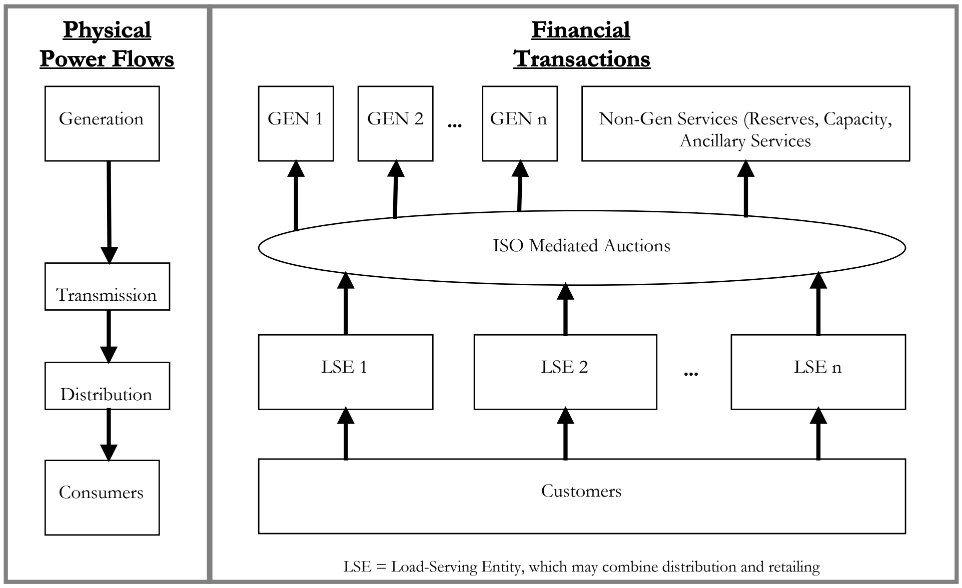
[2] Though the effects obviously propagate up or down the supply chain.

[3] Both calculated from the same ISO report [16].

kets facing varying degrees of regulation. A group of markets which ensure the quality of electricity (including voltage and frequency regulation and back-up generation for unplanned outages) are termed *ancillary services*. While these services are important for a well-functioning power market, they are not the main focus of this investigation. I focus instead on the sales of bulk energy in the form of electricity, which occur at both a wholesale and retail level[4]. In the wholesale market, T&D companies purchase power from generators in a pool, which is mediated by the New England Independent System Operator (ISO-NE). A conceptual map of the power flows and financial transactions which define this market is included in Figure 2-1.

Figure 2-1: New England Market Participants, Power Flows, and Financial Transactions



Wholesale sales include forward contracts (which are not overseen by ISO-NE), a day-ahead market, and a real-time market. In New England, most power is sold in a day-ahead auction, in which generators submit multi-part supply bids, reflecting their fixed and marginal costs, for each hour, and T&D companies submit demand bids. The ISO performs a security-constrained economic dispatch, calculating the least-cost combination of generators that can supply the submitted demand (including transmission losses and congestion effects) and dispatching those plants accordingly. Any shortages between the day-ahead cleared

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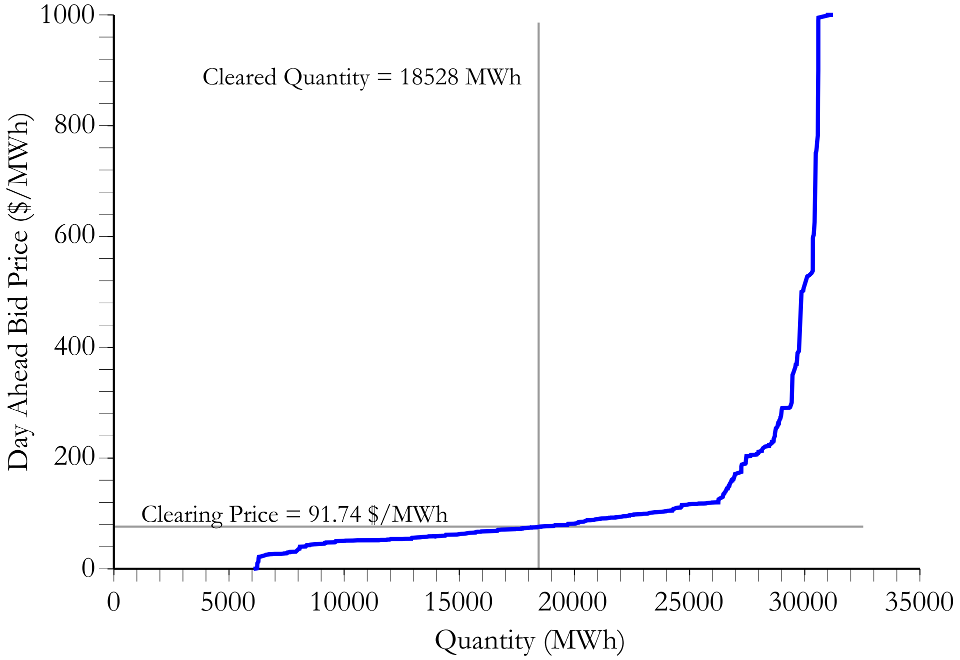
[4] In reality there are sales between these two stages, as transmission, distribution, and retail are not always vertically integrated. The markets modeled in later chapters, though, are the wholesale and retail markets.

quantity and the real-time demand are made up in the real-time market. The marginal cost of power production, then, varies by hour depending on demand and fuel costs. A typical supply schedule for New England (calculated from the cost-ascending cumulative bids of generators) is shown in Figure 2-2.

Figure 2-2: ISO New England Supply Curve for 5PM August 6, 2006



In the retail market T&D companies (or competitive retailers who purchase from aggregators) sell power to end-users. For most customers in New England, the retail price of electricity is fixed at a flat rate by regulators and does not vary throughout the day[5]. End-users have a latent electricity demand that varies throughout the day, depending on activity, temperature, sunlight, etc. This variation in demand, coupled with the steep section of the supply schedule shown at high load factors[6] in Figure 2-2, means that hourly marginal prices on the wholesale market fluctuate significantly throughout the day. End-users are not sensitive to these fluctuations because they face a flat rate. Figure 2-3 shows demand and wholesale clearing prices for three days in New England.

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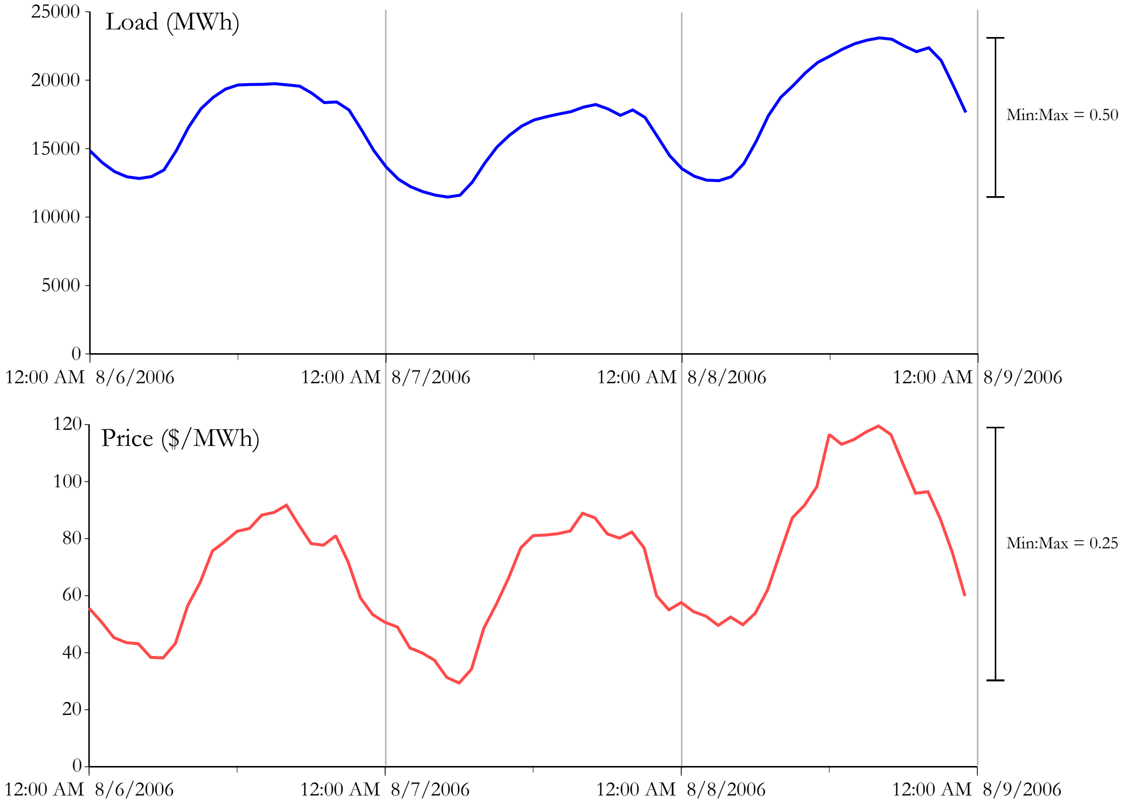
[5] Many large industrial users do face time-of-use tariffs. In this case, price may vary throughout the day but still does not adjust in real time to the marginal conditions of the wholesale market.

[6] *Load Factor* will be used throughout to refer to the ratio of instantaneous demand to system generating capacity.

Figure 2-3: ISO New England Demand and Wholesale Price Over Three Days



## 2.3 Problems with Price-Inelastic Demand

Since end users do not face the true marginal cost of generation in most hours, they do not respond to real prices and their demand with respect to wholesale prices can be considered inelastic. That is

$$\epsilon = \frac{\delta \ln(Q_t(p_t))}{\delta \ln(p_t)} \approx 0 \tag{2.1}$$

where $Q_t(p_t)$ is the demand at hour $t$ and clearing price $p_t$. While consumers do respond to the prices they face, those prices are not the same as the wholesale price $p_t$ (the marginal cost of generation). To see the short-run problem with inelastic demand, refer to Figure 2-4. In this figure, the effect of the flat price is shown as a price control. In two different hours with different latent needs for electricity, consumers may have some high and low demand, represented by the demand curves $D_H$ and $D_L$, respectively. The controlled price is $p_{flat}$, while the uncontrolled prices (i.e. those that would be paid in the wholesale market with elastic demand) are noted with $RTP$. Note that these prices are different than what is actually paid in the current wholesale market (shown with $W$) since the demand is inelastic with respect to the wholesale price. In hours where the wholesale price is higher than the flat price, adding elasticity to the retail market will lower the wholesale clearing price and reduce the quantity sold, while in hours where the wholesale price is lower than the flat price, adding elasticity will increase prices and quantities[7]. In the simple representation of Figure 2-4, the short-run deadweight loss of the flat price policy is shown with the shaded triangles.

In addition to the short-run deadweight loss, flat retail rates create a long-run dynamic inefficiency. Because large quantities of electricity cannot be stored economically, generation capacity must be able to supply the market's peak demand. This implies that plants will be constructed which will only generate in a handful of hours, meaning that capacity utilization will be low and fixed costs per power produced will be higher than they would otherwise be. While restructuring the wholesale market has created incentives to increase the short-run operational efficiency of generation units, it does not address the long-run inefficiencies

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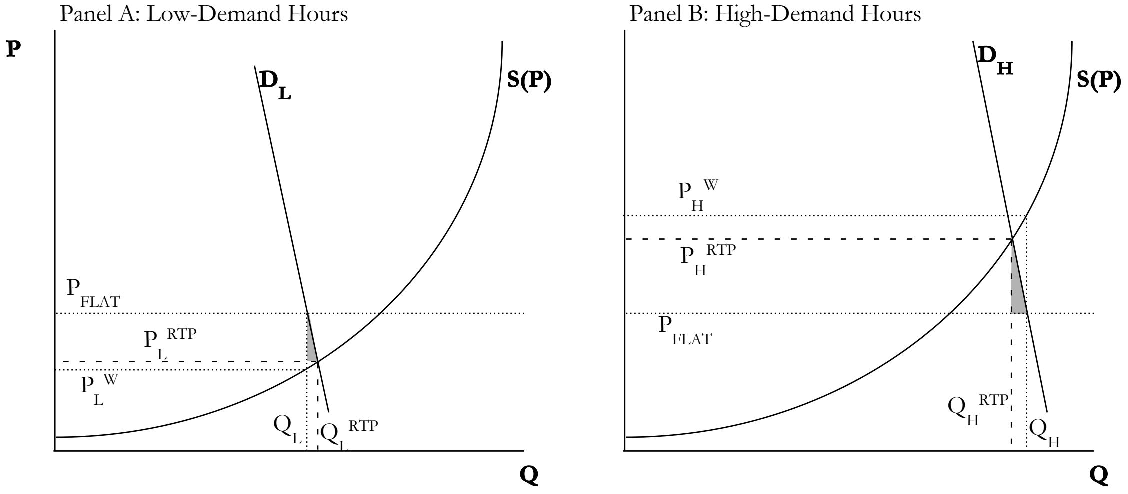
[7] While this discussion and the model developed later in this thesis assume a constant elasticity of response in all hours, some evidence exists that consumers have higher elasticity in peak periods[41]. Even with constant elasticity we have an asymmetric response throughout the day (resulting in lower total quantities consumed, see Chapter 4), and inclusion of a varying elasticity would magnify this effect.

introduced by having to build capacity to generate only in hours of peak demand.

Figure 2-4: Short-run Efficiency of Flat Electricity Pricing



Some economists have also argued that inelasticity of demand creates more favorable conditions for the exercise of anticompetitive behavior in the wholesale market. Economists have noted that when demand is inelastic, generators capture the entire rent that is created when prices rise due to anticompetitive behavior [40, 5]. In contrast, when demand is elastic, increases in price are met with a reduction in demand, such that the expected payoff to anticompetitive behavior should be much lower than with inelastic demand[8].

A final issue with the current market structure is one of equity, in the form of cross-subsidies. End-users whose peak latent demand coincides with system peaks are subsidized by users whose latent demand peaks in hours of lower system demand. The first group uses electricity when the marginal cost of generation exceeds their price, while the second group uses electricity when the marginal cost is lower than the price they pay. The distribution of this burden (subsidized vs. subsidizing) is not necessarily random throughout the population.

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[8] In the New England power pool, all dispatched generators are paid the clearing price, i.e. the amount bid by the marginal generator. In this case, all generators capture rent created by anticompetitive price-inflation at the margin. Other markets are designed differently. For example, the UK wholesale market uses a pay-as-bid rule, where each dispatched generator is paid what they bid, rather than the market clearing price. In a single auction where only the marginal unit exercises market power, only that unit will capture anticompetitive rent. However, in repeated auctions one expects the auction participants to infer one another's bidding strategy, allowing the infra-marginal units to raise their bids and, hence, what they are paid. When the marginal unit(s) behaves anticompetitively, infra-marginal units may learn to inflate their bids over the competitive clearing price, leading to the same result as the single clearing-price auction. This result has been shown in a number of ways [37, 36, 26]

In California, for example, the subsidy flows from coastal population areas (where moderate temperatures translate to lower peak demand) to the Central Valley (with its high peak-coincident demand for air conditioning) [5]. While this redistribution may or may not be desirable on a case-by-case basis, the point here is that it is not a result of deliberate political processes.

## 2.4 Real-time Pricing as Market Remedy

One policy that has been proposed to address the issues of inelastic demand is real-time pricing (RTP) for end-users. RTP would require that retail companies track end-use by time (typically by hour) and charge end users a price that reflects the marginal cost of generating electricity during that time. In other words, consumers would pay the wholesale-market clearing price plus some transmission and distribution mark-up which may or may not vary with time-of-use or demand. Benefits of this policy (which I discuss in more detail in the following chapters) have been cited widely [40, 5] and include:

- Reducing long-run dynamic inefficiencies and therefore long-run electricity costs,
- Reducing the need for rationing via blackouts in times of structural supply shortages,
- Possibly reducing short-run electricity costs for the average consumer, and
- Reducing incentives to exercise market power.

Similar alternative policies including time-of-use pricing, peak pricing, and critical peak pricing have been reviewed elsewhere [40, 4]. In general these policies approximate RTP but do not achieve the same level of benefits while costing a similar amount, a result which has been shown in the short run [21] and long run [6]. This thesis will therefore focus exclusively on RTP[9].

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[9] Though, since all these policies have the same basic effect – reducing peak demand through price response – we would expect most results to be qualitatively similar across policies.

## 2.5 Hypothesized Impacts of Real-Time Pricing

The next chapter will review the literature on the effects that RTP adoption would have on various market participants, but before getting into these details I will state the hypothesis that motivated the original research. By introducing price-elasticity in retail sales, RTP should

- Increase both quantity and wholesale price in those hours with a wholesale price lower than the regulated flat retail rate, and
- Decrease both quantity and wholesale price in those hours with a wholesale price higher than the regulated flat retail rate.

In New England, peak demand (and hence hours with wholesale price greater than retail price) typically occurs in the afternoon or evening while periods of lowest demand occur in the middle of the night, and demand typically peaks during summer months. The expected wholesale price changes due to RTP should therefore exhibit both diurnal and seasonal patterns, which could translate into revenue impacts for intermittent renewable generators whose resource varies daily or seasonally which are significantly different than the revenue impacts on non-intermittent generators (such as fossil). For example, solar generators may be particularly hurt because their resource is most available in high-demand afternoon hours, while wind may benefit if it is more available at night or during the winter.

My hypothesis with respect to renewable generators can be stated as follows:

- $H_0$: The effect of RTP on intermittent renewable generators will be no different than the average effect on producer revenues
- $H_1$: Solar generators will be particularly harmed by RTP, while some wind sites may benefit from RTP

The effect that RTP would have on environmental impacts of electricity generation is also of interest. Peak generation in New England is typically supplied by a mix including older (and more-polluting) oil plants, while intermediate generation is supplied by a mix of gas and coal which may have cleaner emissions. If the response in peak and off-peak hours, then, is symmetric (or skewed to greater response in off-peak hours), we might expect emissions to decrease due to RTP.

My hypothesis with respect to emissions can be stated as follows:

- $H_0$: RTP will have no effect on gross annual emissions
- $H_1$: RTP will decrease gross annual emissions

## 2.6 Central Questions

In order to test my first hypothesis I frame my analysis as a retrospective question:

> *What would producer revenues, and in particular renewable generator revenues, have been if end-users were charged real-time prices?*

In Chapters 4 and 5 I answer this question by modeling the counterfactual for the period 2003-2006.

My second hypothesis is investigated similarly. I seek to answer the question:

> *How would emissions have changed if end-users were charged real-time prices?*

To answer I use the counterfactual model developed in Chapter 4 and marginal emissions rates developed in concurrent work. This is the focus of Chapter 6.

These analyses improve our ability to answer a larger question of political economy:

> *Given that real-time pricing is a welfare-improving policy, what barriers prevent its implementation?*

In Chapter 7 I draw on my empirical analyses and literature from political science and economics in order to address this question.

# Chapter 3

# Welfare, Equity, and Environment Effects of Dynamic Pricing

RTP and other dynamic pricing schemes have been the subject of much study and experimentation over the last 25 years. In the following sections I summarize the existing literature on welfare and environmental impacts of RTP. I close with a shorter summary of experience with RTP in the United States, in both experimental and real (i.e. profit-seeking) settings.

## 3.1 Welfare Effects of Real-Time Pricing

Economists have modeled the welfare and competitive effects of RTP with both a short-run and long-run perspective. In the following paragraphs I summarize a few of these analyses in order to outline the economic benefits of RTP.

Holland and Mansur [21] studied the short-run efficiency effects of RTP with a simulation model based on the 1998-2000 PJM market (Pennsylvania, New Jersey, Maryland, and Delaware). Their model estimates the daily supply schedule in the wholesale market using plant efficiency, fuel prices, and pollution-permit prices from public data sources[1]. The demand schedule for each hour is identified by the reported system load and an assumed

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[1] This method of estimating the supply curve is used in a number of studies of market power in wholesale electricity markets [25, 44, 9], in which it is termed *Competitive Benchmark Analysis*. This method assigns daily input costs to each generating unit in a market and recreates the supply schedule by aggregating all units' marginal cost curves. This method is different than the one I use in Chapter 4.

constant-elasticity of demand, with a non-zero own-price elasticity and zero cross-price elasticity (i.e. consumers are assumed to respond to price within the hour, but not substitute use in one hour for use in another). Specifically, their model uses the form

$$D_t = A_t * P(D_t)^{\epsilon} \tag{3.1}$$

to represent demand for those consumers on RTP, where $D_t$ is the quantity demanded in time $t$, $A_t$ is the parameter which locates the demand curve in each hour based on the observed demand in hour $t$, $P(D_t)$ is the market clearing price given quantity $D_t$, and $\epsilon$ is the own-price elasticity of demand.

The authors evaluate a counterfactual for the model period - what would prices and quantities have been if consumers faced RTP? They test a range of elasticities and a range of RTP penetration. A summary of their results is reproduced in Table 3.1, where the "Increased Surplus" is measured for all consumers, as a fraction of the total electricity bill they faced under a flat tariff. At a societal level, they find that the deadweight loss of flat retail prices represents 0.24% of the total electricity bill, assuming an elasticity of -0.1[2] and full penetration of RTP. In other words, total surplus is increased by .24% of total electricity sales by introducing RTP to all customers. For the PJM wholesale market, with total annual sales of $7 billion [21], this loss represents only $17 million. The short-run efficiency gains of RTP, while positive, are therefore likely to be small.

Holland and Mansur also report welfare effects with a subset of the population on RTP. These results are reported in Panel B of Table 3.1. In the short run, they find that there are decreasing returns – in terms of lowering average price – to increasing the fraction on RTP, but constant returns in terms of welfare effects. The model described in Chapters 4-6 considers only full penetration of RTP, but these results suggest that there are societal benefits to having any fraction of consumers on RTP. In Appendix C I show how the aggregate demand curve changes with a fraction of consumers on RTP.

Borenstein and Holland [10] and Borenstein [6] find greater societal benefits in the long-run. Their models use a similar formulation of demand schedule, but they estimate the

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[2] Dahl [15] produced a widely-cited meta-survey of elasticity estimates for electricity demand. According to this work, -0.1 represents a reasonable short-run elasticity.

Table 3.1: Short-Run Welfare Effects of RTP in Classic PJM Market: 1998-2000

Panel A: Varying Elasticity with 100% of Customers on RTP

| Scenario | Mean Hourly Load | Mean Hourly Price | Increased Surplus as % of Energy Bill, for All Consumers |
|---|---|---|---|
| Flat Tariff | 29.9 GW | \$65.20/MWh | - |
| RTP, $\epsilon = .05$ | 0.06% | -0.15% | 0.13% |
| RTP, $\epsilon = .10$ | 0.18% | -0.55% | 0.24% |
| RTP, $\epsilon = .20$ | 0.42% | -0.74% | 0.45% |

Panel B: Varying % of Customers on RTP with $\epsilon = .10$

| % on RTP | Mean Hourly Load | Mean Hourly Real-Time Price | Increased Surplus as % of Energy Bill, for All Consumers |
|---|---|---|---|
| 0% | 29.9 GW | \$65.20/MWh | - |
| 33% | 0.10% | -0.38% | 0.08% |
| 67% | 0.14% | -0.46% | 0.16% |
| 100% | 0.18% | -0.55% | 0.24% |

*Table summarizes Holland and Mansur's results [21]. Numbers shown for counterfactual RTP scenarios are changes relative to the flat-rate scenario.*

supply schedule using average costs for three classes of generators (baseload, intermediate, and peak) rather than unit-specific data based on the existing generation stock. They allow the mix of generation units to vary and solve for the equilibrium investment in baseload, intermediate, and peaker plants.

The short-run model discussed above takes the capital stock of generating units as fixed and evaluates the effect of a behavioral response to RTP. In contrast, this long-run model allows both consumer- and long-run investment-behavior to vary. While the long-run model is parameterized to resemble the classic PJM market, it is an equilibrium rather than simulation model. As above, the authors test a range of elasticities and RTP penetration. A summary of their results is reproduced in Table 3.2, which shows market-level effects on price and quantity, and Table 3.3, which shows the effect of RTP on the long-run investment equilibrium of base vs. intermediate vs. peak plants.

Table 3.2: Long-Run Welfare Effects of RTP in Classic PJM Market: Future Equilibrium

| Panel A: Varying Elasticity with 99% of Customers on RTP | | | |
|---|---|---|---|
| Scenario | Mean Hourly Load | Mean Hourly Price | Increased Surplus as % of Energy Bill, for All Consumers |
| Flat Tariff | $26.4 \times 10^6$ GWh | $39.7 \times 10^{15}$ \$/MWh | - |
| RTP, $\epsilon = .10$ | 1.2% | -7.7% | 5.9% |
| RTP, $\epsilon = .30$ | 3.3% | -13.1% | 9.7% |
| RTP, $\epsilon = .50$ | 5.2% | -15.6% | 12.0% |
| Panel B: Varying % of Customers on RTP with $\epsilon = .10$ | | | |
| % on RTP | Mean Hourly Load | Mean Hourly Real-Time Price | Increased Surplus as % of Energy Bill, for All Consumers |
| 0% | $26.4 \times 10^6$ GWh | $39.7 \times 10^{15}$\$/MWh | - |
| 33% | 1.7% | -7.1% | 5.6% |
| 67% | 2.7% | -10.7% | 8.0% |
| 99% | 3.3% | -13.1% | 9.7% |

*Table summarizes Borenstein's results [6], which reflect the long-run investment equilibrium in some future year. Numbers shown for RTP scenarios are changes relative to the flat-rate scenario.*

RTP has large long-run welfare benefits. With the conservative elasticity estimate of

Table 3.3: Long-Run Equilibrium Investment Levels with RTP in Classic PJM Market

| Scenario | Total Annual Consumption (billion GWh) | Equilibrium Capacity (GW) Baseload | Intermediate | Peak |
|---|---|---|---|---|
| Flat Tariff | 231 | 27.0 | 5.4 | 14.6 |
| RTP, $\epsilon = .10$ | 234 | 27.5 | 4.6 | 3.4 |
| RTP, $\epsilon = .30$ | 239 | 28.6 | 1.8 | 0.0 |
| RTP, $\epsilon = .50$ | 243 | 29.0 | 0.0 | 0.0 |

*Table summarizes Borenstein's results when all consumers are on RTP [6].*

-0.1, they find total surplus is increased by 6% of total electricity sales with all customers on RTP. A more likely long-run elasticity is -0.5[3], and with this parameter the authors estimate a 12% increase in total surplus as a percentage of total electricity sales. With even a subset of the population on RTP, large welfare gains are expected. For example, with only 33% of consumers on RTP the authors find approximately 60% of the welfare gains that are achieved in the full-penetration scenario (see Panel B).

These welfare benefits are achieved by shifting equilibrium investment toward a more efficient generation mix. By lowering the volatility of demand, RTP encourages a higher fraction of the generating infrastructure to be made up of baseload plants with lower variable costs — 100% in the high-elasticity scenario versus less than 60% in the flat-tariff scenario as shown in Table 3.3. As elasticity increases, equilibrium investment is skewed more to baseload capacity and total capacity is decreased. This shift produces the savings which translate into increased surplus. Compared to the cost of adding real-time meters, the welfare increase is large[11, 6]. The long-run economic efficiency gains therefore justify the RTP policy from a societal perspective.

The short-run and long-run models discussed above make two important assumptions. First, they exclude any considerations of anticompetitive behavior by generators when bidding in the wholesale market. As discussed previously, anticompetitive behavior is expected to be more attractive to generators when demand is inelastic. A model that ignores anti-

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[3] Based on the Dahl [15] survey cited previously.

competitive behavior, therefore, systematically underestimates the wholesale clearing price during peak hours. Including a consideration of anticompetitive behavior would increase both short-run and long-run welfare gains, since elastic consumers will be less exposed to oligopoly rents and generation investment incentives will be less distorted by the potential for extracting those rents. Second, they ignore any inter-hour substitution which might take place, modeling only the consumer's within-hour price response. Evidence in this chapter and discussed further in Chapter 4 suggests that this is a reasonable assumption, but to the extent that inter-hour substitution takes place these models will underestimate welfare gains by underestimating consumer response.

### Summary of Societal-Level Effects

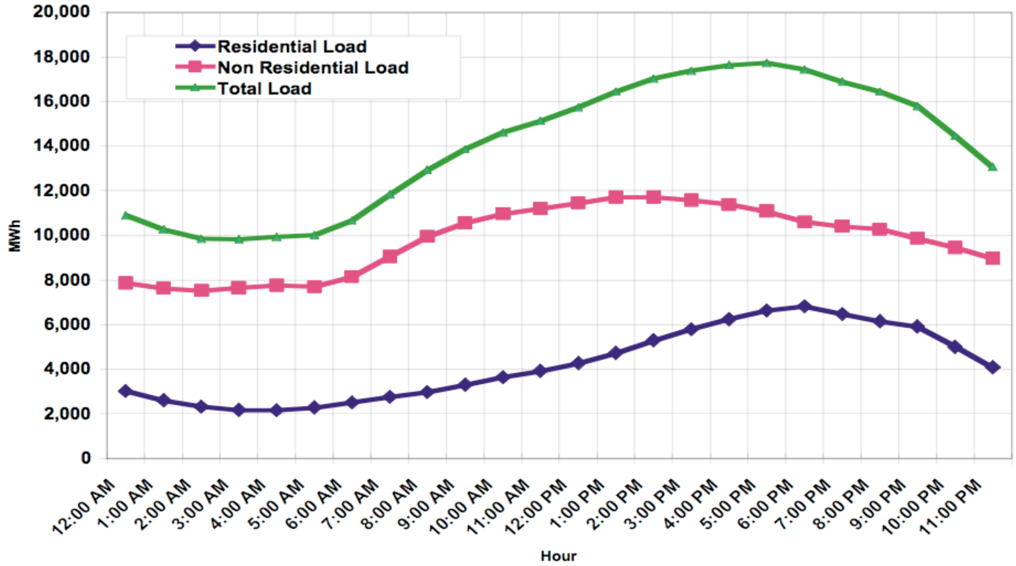
RTP is expected to have moderate but positive short-run effects while consumers have low capacities to respond to price (and hence low intra-hour price elasticity). Peak prices are expected to fall and mean demand is expected to increase moderately. In the long-run, as investment in the generation mix equilibrates, RTP is expected to create significant increases in total surplus by incentivizing more economically efficient use of generation assets.

## 3.2 Consumer Welfare and Consumer Response to Real-Time Pricing

While RTP is expected to increase economic welfare (by correcting market distortions), it will not necessarily have positive effects for all participants in the market. Below I summarize the expected effects for some classes of consumers, based on both theoretical and experimental inquiries in the literature.

In general, consumers whose individual peak demands coincide with peak prices and have inelastic demand characteristics will be hurt by RTP, while those whose peak demand falls in hours of lower prices or those with the ability to respond to prices (i.e. those with elastic demand characteristics) will benefit from RTP. Figure 3-1, which is copied from Borenstein et al [11], shows the demand profile of residential and commercial users in California, compared

Figure 3-1: Load Profile of Residential and Commercial Customers in California.



with the total system load. Note that peak residential use appears to be more coincident with the system load than commercial use, so in this region residential users are likely to have more of their use occur in high-price hours. Residential users are more likely to have a higher elasticity [15], however, so to an extent they are behaviorally capable of avoiding some exposure to high prices.

The net effect on residential versus commercial end-users, therefore, is unclear and may vary more across individuals within each consumer class than across classes. For example, Borenstein [8] has analyzed observed demand data by hour for 1142 industrial customers of the Pacific Gas and Electric (PG&E) company in California. These users represent some of the largest PG&E customers and their current rate structure from PG&E is typically Time-of-Use (TOU), where rates vary by time (usually with a peak and off-peak price) but are adjusted infrequently by regulators and do not immediately reflect the actual marginal cost of generation in any particular hour. Borenstein calculates what each customer's total bill would have been from 2000-2003 if that customer paid real-time prices (i.e. the prices observed in the wholesale market during that period) instead of flat prices, then examines the distribution of the change in consumer surplus among the customers. The results are summarized in

Figure 3-2: Distribution of Change in Electricity Bills from Implementing RTP, Compared to Flat Tariff

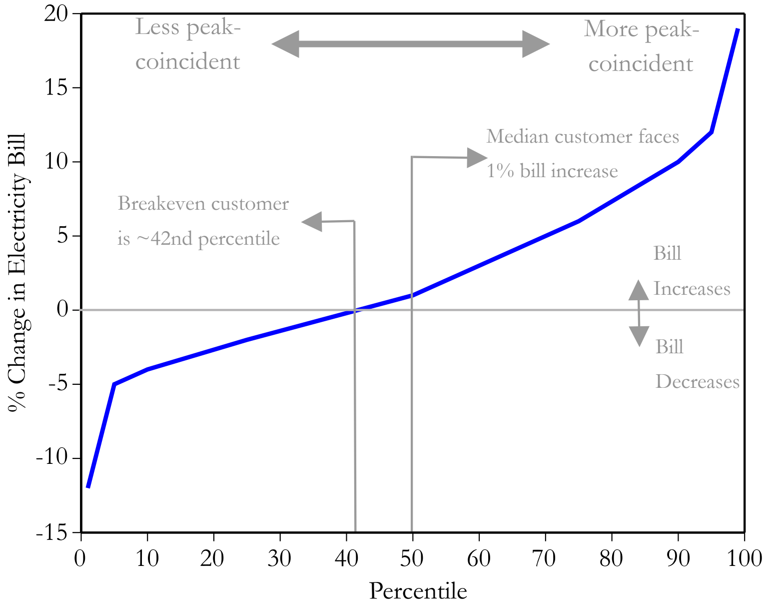


Figure 3-2, which was created from data in Borenstein [8][4]. In the worst case of zero elasticity for all users[5], Borenstein finds that the upper quartile of customers face electricity cost *increases* of at least 6% and up to 19% of their flat-rate bill, while the lowest quartile gains *savings* of at least 2% and up to 12%. By increasing the assumed elasticity, though, Borenstein finds that the number of customers with higher bills and the maximum bill increase faced by any one customer under RTP both decrease. In other words, as the elasticity of individual consumers increases, the share of consumers who have positive changes in their individual surplus increases. These results suggest that heterogeneity among customers in both load profiles and ability to respond to prices will be important in determining which end-users win and lose due to RTP.

Another econometric investigation of industrial customers' responses to RTP [41], in the Duke Power service area of the southeast United States, found similar variability in response. The authors collected hourly price and demand data from 51 large industrial customers who were on Duke Power's optional RTP tariff for up to eight years and estimated separate own-

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[4] The series plotted in this figure is derived from Borenstein's simulated price series. He presents an alternative analysis using observed prices, with which the results are qualitatively similar.

[5] Zero elasticity is worst-case in that it implies maximum wealth transfer because each customer is exposed to the greatest costs. Any elasticity would allow users to respond to high prices and therefore reduce their total electricity bill.

and cross-price elasticities[6]. Of interest in this discussion are two aspects of their findings. First, the estimated cross-price elasticities are at least an order of magnitude less than own-price elasticities, a finding which will be used to justify assumptions in the model developed in Chapter 4. Second, and of more interest now, is that behind the *average* elasticities are large variances in the elasticities of the *individual* consumers. For example, the range of peak-period own-price elasticities estimated for customers within the textile sector varies by a factor of 43 , from -.008 to -.35. These findings again support the assertion that the characteristics of individual consumers are more important in determining consumer effects of RTP than an analysis based on consumer classes.

### Summary of Consumer Effects

The effects of RTP on consumers are likely to vary at least as much across customers within a particular class than across classes of customers. We expect that:

- Consumers whose latent demand is peak-coincident and are not able to respond to prices will face significantly higher bills under RTP.
- Consumers whose latent demand is off-peak-coincident will face lower bills under RTP.
- Consumers who are able to respond to high prices may face lower bills, even when their latent demand is peak coincident.

## 3.3 Producer Welfare and Real-Time Pricing

The gains or loses to producers, on the other hand, are likely to be more systematic by class. Revenues to baseload, intermediate, and peak generators are likely to change in different ways. To the extent that RTP is successful in flattening a system's load over time, peak generators will be less necessary during high-demand periods and capacity utilization of

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[6] Instead of the CES model described above, the authors estimate the Generalized McFaddon functional form, which allows them to estimate separate own-price elasticities for each hour of the day, along with separate non-zero cross-price elasticities (i.e. the measurement of substitution between hours based on relative prices in those hours). Their own- and cross-price elasticities for the sample of all customers are shown in the original paper [41].

baseload generators will increase during off-peak hours[7]. Holland and Mansur [21] use the short-run model described above to analyze the differential effects of RTP on coal, gas, and oil generators' operating profits. Their results are summarized in Table 3.4. The authors find that expected profits for the generation sector as a whole decrease by 9% during the 2 years analyzed, assuming 100% of customers are on RTP. This effect varies significantly as coal, gas, and oil expected profits decrease by 5%, 34%, and 59%, respectively, when using a moderate elasticity of -0.1. Chapter 5 reports a complementary analysis based on my model of the New England market.

Table 3.4: Short-Run Effects of RTP on Producer Profit by Fuel, Classic PJM Market

| | Average Hourly Profit | | |
|---|---|---|---|
| Scenario | Coal | Gas | Oil |
| Flat Tariff | 147225 | 4055 | 13688 |
| RTP, $\epsilon = .05$ | -1.42% | -10.24% | -20.00% |
| RTP, $\epsilon = .10$ | -4.79% | -34.19% | -59.10% |
| RTP, $\epsilon = .20$ | -6.22% | -43.02% | -70.46% |

*Table summarizes results in Holland and Mansur [21]. Numbers shown for RTP scenarios are changes relative to the flat-rate scenario. Profit is reported for all capacity by fuel-type, rather than per MW installed.*

## 3.4 Consumer Risk and Hedging Possibilities

In addition to first-order economic impacts, consumers may be concerned about the risks associated with a shift to RTP, in the form of bill volatility and exposure to high-prices with insufficient notice. Even as total bills fall for consumers as a whole, risk aversion may contribute to significant resistance to RTP unless sufficient hedging mechanisms are offered. Borenstein [7] examined demand data from 1142 large industrial consumers in California

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[7] In the short run, marginal generation units may be forced to bid even higher prices due to their lower capacity utilization. This may be self-defeating, as a steeper supply schedule at the margin will induce an even larger price response. The short-run models discussed in this chapter, as well as the one developed in Chapter Four, do not include this supply response – producer behavior is held exogenous – while the long-run equilibrium model captures a period after the generation stock has turned over. An opportunity therefore exists for more work in this area – developing a dynamic short-run model with endogenous producer behavior.

from 2000-2003 in order to evaluate the counterfactual – what would bill volatility have been had each consumer faced RTP, with and without a simple hedging mechanism? He found that RTP with no hedging would significantly increase monthly bill volatility for these consumers, but that an actuarially-fair forward electricity contract could reduce this volatility significantly. These results suggest that while consumer risk from RTP is real, it could be dealt with via relatively simple hedging arrangements.

## 3.5 Non-Economic Impacts of Real-Time Pricing

In addition to economic benefits, RTP may to alter some environment and health impacts associated with electricity generation. As I discuss below, these effects are mixed. In many generation systems, the last plants to be dispatched may be older, less efficient, and more polluting than average. Any short-run environmental benefits of RTP are therefore derived primarily from lowering system load during the highest-demand hours, when these dirty peak generators would have been dispatched. At the same time, RTP is expected to increase load, and therefore total emission rates, in low-demand hours. Holland and Mansur [21] used the short-run simulation model described above to estimate the effect of RTP on emissions in the classic PJM market. A summary of their results is reproduced in Table 3.5. Using moderate elasticities and assuming all customers are on RTP, the authors find that the increase in emissions during low-demand hours just outweighs the decrease in emissions during high-demand hours, creating small (<1%) increases in net $SO_2$ and $NO_x$ emissions and a similarly small decrease in $CO_2$ emissions.

Table 3.5: Short-Run Environmental Effects of RTP in the Classic PJM Market

| | Change relative to Flat-Tariff Emissions | | |
|---|---|---|---|
| Fuel | $SO_2$ | $NO_x$ | $CO_2$ |
| All Fossil | +0.75% | +0.26% | -0.16% |
| Coal | +1.28% | +1.33% | 1.29% |
| Oil | -13.08% | -17.89% | -17.94% |
| Gas | -5.34% | -6.87% | -5.58% |

*Data summarizes Holland and Mansur's[21] results.*

In another empirical analysis using econometric rather than data-mining techniques, Holland and Mansur [22] find small associations between load variance and emissions of $SO_2$, $NO_x$, and $CO_2$ in all power regions of the United States, with the sign of the associations dependent on the characteristics of the generation system in the region. For example, lower demand variance is associated with lower emissions of all three pollutants in the Mid-Atlantic, a region that relies on oil for peak generation, while Western regions, which use gas and hydro for peak generation, have a negative association between demand variance and emissions. Their results are summarized in Table 3.6. The numbers reported are the association of decreasing load variation with emissions, estimated via regression. The estimated model controls for linear and quadratic load, temperature, monthly fixed effects, and autoregression, and is estimated separately for each region.

While these analyses suggest RTP may increase emissions, the timing of emissions (especially $NO_x$) may determine whether or not the overall effect is harmful. Martin [30] explains how the real impact of $NO_x$ emissions depends on other factors that are dynamic in time, such as VOC emissions and sunlight. While I will not address these effects, I suggest that a more thorough analysis might consider not just absolute emissions levels but also timing and interaction effects among pollutants.

The long-run environmental effects of RTP are even less certain, and this topic has not been well studied. Three competing effects are obvious, and others may emerge in subsequent research. The largest effect may be rebound – by improving economic efficiency and lowering average retail prices, RTP should lead to an increase in total demand for electricity in the long run. In the long-run, electricity demand may be three times more elastic than in the short run [15], so to the extent that future electricity is supplied by fossil sources, rebound means that RTP may end up increasing long-run emissions even more than the short-run changes modeled by Holland and Mansur [22, 21]. A second effect in the opposite direction comes from the reduced need for peak generation capacity. Adding new capacity creates environmental impact in the form of land-use change, emissions during the fabrication of the generating units, emissions from the construction of the plant and its fueling infrastructure, and impacts associated with extending the transmission system. By reducing the need for generation capacity, RTP reduces these impacts. A third long-run environmental effect is

Table 3.6: Correlation of Within-Day Load Variation and Emissions by Region

Dependent variable: Columns (i-iii) log of daily emissions in daily pounds of emissions.
Independent variable: Negative log of the coefficient of variation (std. dev. over mean).

| Region | (i)<br>$SO_2$ | (ii)<br>$NO_x$ | (iii)<br>$CO_2$ |
|---|---|---|---|
| Lower variance associated with higher emissions: | | | |
| East Central Area | 0.025* | 0.020* | 0.016* |
| Mid-Continent Area | 0.012 | 0.022* | 0.022* |
| Southeast | 0.028* | 0.015* | 0.010* |
| West | 0.042* | 0.027 | 0.024* |
| Texas | 0.036* | -0.008 | 0.009* |
| Lower variance associated with lower emissions: | | | |
| Florida | 0.028 | -0.033* | 0.013 |
| Mid-Atlantic | -0.009 | -0.035* | -0.041* |
| Mid-American Interpool | -0.027* | -0.037* | -0.031* |
| Uncertain association: | | | |
| Northeast | 0.015 | -0.047 | -0.001 |
| Southwest | 0.001 | -0.005 | -0.001 |

Notes from original source:
"Table presents GLS coefficients accounting for a common AR(1) error structure using Prais-Winsten method. We note significance at 5% level using (*). Regression includes month-year fixed effects, quadratic function of log of daily mean quantity demand, and daily mean, minimum, and maximum temperatures for all states bordering each region."

Table excerpted from Table 4 in Holland and Mansur [22] the differential economic impact that RTP may have on renewable generators. If RTP makes solar or wind more profitable relative to fossil generation, normal market forces will favor the construction of more renewable generation capacity. An analysis of this effect is discussed in more detail in the following chapters.

Finally, RTP may offer security benefits that have not been well studied. These benefits are derived from shifting power production from peak generators, which use imported fuels (oil and gas) with high price volatility, to baseload generators, which use domestic fuels with less price volatility. RTP therefore reduces exposure to risks such as price spikes, embargoes, and terrorist attacks on energy infrastructure abroad, as well as reducing the need for additional LNG terminal construction in the US.

## 3.6 Summary of Published Real-Time Pricing Effects

The societal impacts of real-time pricing as described in the literature are therefore summarized as:

- A moderate improvement in short-run and a significant improvement in long-run economic welfare.
- A reduction in the incentives to exercise market power in wholesale auctions.
- A possible reduction in peak emissions rates, but close to zero effect on overall emissions in the short-run and mixed environmental effects in the long run.
- A possible relative advantage for wind and solar producers, but an overall decrease in generator revenues.
- Some security benefits that have not been well studied.

While alternatives to RTP exist (such as Time of Use pricing), the studies cited above found that the welfare impacts of these alternatives are significantly attenuated relative to RTP, while the implementation costs are similar. For example, compared to the RTP welfare gain of 0.24% calculated in Holland and Mansur [21], TOU achieves a modest 0.03% welfare gain and monthly flat-rate adjustments (rather than annual) achieve a 0.07% welfare gain.

RTP is therefore a preferred policy among those who value economic efficiency most highly. Those who value the environment may not like the possibility of increased emissions over the long-run, but this increase is really due to RTP's amplification of an existing market failure (i.e. electricity users do not pay for environmental externalities) rather than a root problem with RTP itself.

## 3.7 Experience with Real-Time Pricing

Lest RTP seem an academic curiosity based on the above discussions, in this section I briefly highlight some of the many implementations of RTP in the United States. In addition to the Duke Power experience discussed above [41], RTP has been offered by a number of utilities to both industrial and residential consumers, sometime as an experiment but, increasingly, with purely profit-seeking motivations. Early examples include Pacific Gas and Electric offering a variety of dynamic pricing tariffs to some of its residential customers in the 1980's [42] and the Niagara Mohawk Power Company setting RTP as its default service for large industrial customers starting in 1998 [23]. More recently, a number of individual utilities and entire states have set or plan to set RTP as the default service for the largest consumers. A summary of these plans (adapted from Barbose et al 2004 [2]) is included as Table 3.7. While most customers have chosen to opt out of this service [2], the fact that it is offered this widely is a recent development, and an average of 15% of the customers in these service areas for whom RTP is the default have remained on the RTP tariff.

Table 3.7: Current RTP Default Service in the United States

| State | Utilities | Starting Year | Applicable Customers |
|---|---|---|---|
| New York | NMPC | 1998 | >2,000 kW |
| New Jersey | Statewide | 2003 | >1,250 kW |
| Maryland | Statewide | 2005 | > 600 kW |
| New York | CHG&E | 2005 | >500 kW |
| Pennsylvania | Duquesne | 2005 | >300 kW |
| Delaware | Statewide | 2006 (planned) | Transmission-level voltage |
| New York | All Others | 2006 or later | Varies |
| Illinois | ComEd | 2007 (planned) | >3,000 kW |
| Pennsylvania | All Others | 2007 or later | >500 kW |

*Data from Barbose et al [2].*

# Chapter 4

# A Model of Real-Time Pricing in the New England Power Pool

## 4.1 Introduction

In the first chapter I outlined the three central questions that this research will address. First, what impact would RTP have on the expected revenues of intermittent, renewable generators, particularly in comparison to the generation sector as a whole? Second, what impact would RTP have on pollutant emission rates? Finally, how will these and other impacts on producers and consumers influence the political support for RTP? The first question is the focus of this and the next chapters, in which I develop a retrospective approach to evaluating the counterfactual: what *would* have been the demand, wholesale prices, and renewable revenues *if* RTP were the mandatory tariff for all customers. In this chapter I describe the first stage of my analysis— modeling changes in the day-ahead energy market due to RTP. First, I describe the microeconomic theory behind the model. Then, I describe the development of the input dataset and the modeled market-level results. The second stage of the analysis, translating market-level changes to firm revenues differentiated by fuel type, is the subject of the next chapter.

## 4.2 Key Assumptions Defining Model Boundary and Form

In order to assess the market-level impacts of RTP, I develop below a simplified model of the day-ahead hourly energy market. The methodology presented in the next section makes a number of important assumptions, each of which is discussed below. In this discussion, it is important to recall that the purpose of this analysis is not to make investment-grade forecasts of the financial implications of RTP, but rather to develop a general intuition for how the availability of intermittent electricity sources covaries with expected changes to wholesale power prices attributable to RTP.

### Market Scope

The first simplification is in defining the model boundary to include only the day-ahead energy market. By doing this, I ignore markets in other periods and for other products. Specifically, I ignore transactions in the futures and spot markets, and I ignore transactions for ancillary services, forward capacity, and demand response. In the period of 2003-2006, the day-ahead market cleared 91% of the ISO-NE total reported load[1], so limiting the analysis to this period captures the overwhelming majority of energy sales[2]. Note, though, that this is not necessarily the case for other regions. The California power pool, for example, relies more heavily on the spot market while other regions such as the PJM market may rely more on long-term contracts or other vertical arrangements [12, 28]. For the ISO-NE region, though, the chosen boundary will model the vast majority of an average generator's revenues endogenously.

### Production Constraints and Non-Convex Costs

The second important simplification is the boundary I choose *within* the day-ahead market. In reality, ISO-NE takes not just energy bids but also system state into account when de-

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[1] Calculated using ISO-NE data.

[2] Note that power may actually change hands more than once between producer and end-user. For example, electricity traders may buy forward contracts from generators and sell their rights to power in the day-ahead market.

termining the day-ahead dispatch. Specifically, it considers which plants are already on or off, and the costs (in addition to marginal input costs) of turning those plants off or on, or ramping them up or down. The model will be used to find the market changes due to RTP, so by leaving out startup and ramping costs, I implicitly assume that their market effects will remain unchanged by RTP.

In reality, startup and ramping constraints are important determinants of system dispatch, as they introduce cost non-convexities into the production functions of each firm or generator. When startup and ramping constraints are considered, there may be times when system operators choose to operate a high-marginal cost unit for a short period of time rather than start a lower-marginal-cost unit with a higher startup cost or time. At other times, units may be run for a short period even when the hourly clearing price is below their marginal costs, operating at a nominal loss in order to avoid incurring shut-down and startup costs. For this reason we may expect the hourly volatility of clearing prices in a model which ignores startup and ramping constraints to be biased downwards compared to the observed volatility. This assumption is consistent with other studies of RTP in restructured markets [10, 21].

## Market Power

I also omit any explicit model of market power in the day-ahead market. Restructured power markets may be more susceptible to oligopoly behavior than other commodity markets because the good sold (i.e. power) cannot be stored and the end-user (under flat pricing schemes) is not sensitive to short-run marginal costs, while the retailer is under regulatory obligations to provide any amount of power demanded, whatever the production cost. Oligopolists may push power prices up *or* down depending on firm structure. In a single-price auction, generators with assets in both baseload and peak classes have significant incentives to inflate the bids of their peak units in order to capture rent with their price-taking assets[12]. At the same time, vertically integrated firms with both generation assets (or long-term contracts) and transmission and distribution obligations, and who are net purchasers of power, have incentives to deflate the bids of their marginal units, selling a small amount of power at a loss in order to drive down clearing prices and therefore increase the margins of their T&D operation [12].

While the first pressure is likely greater (resulting in higher clearing prices due to oligopoly behavior), there is uncertainty over the magnitude of the effect. Bushnell and Saravia [13] estimate the effect of oligopoly behavior in the New England market using a competitive benchmark analysis, which estimates the variable costs of production and compares the observed price to that estimate. They calculate a 12% markup due to market power in the New England market. Competitive benchmark analysis, though, may overestimate the effects of market power by ignoring startup and ramping constraints [29]. When these constraints are considered, efficient dispatch may result in prices that appear inefficient compared to the naive benchmark. In an analysis of the PJM market, Mansur [29] finds that competitive benchmark analysis may overstate the markup due to oligopoly behavior by three to four times. The markup in the New England market, therefore, is likely to be small and in the range of 12%[3] to 3%[4].

Furthermore, market power is likely to decrease under a RTP regime[5]. Increasing demand elasticity should decrease the incentive to exert market power, since consumers will now respond to increased prices by reducing demand.

By using historic ISO-NE data, I implicitly assume that any market power that has existed in the day-ahead market will remain in an RTP regime. While this assumption is made for analytic convenience, I submit that since market power seems limited in ISO-NE markets, the change in gaming due to increased demand elasticity will have little effect on the central analysis of renewable generator revenues. In Appendix C I present a simple example of how changes in market power might be modeled in this simulation. My results suggest that changes in price or quantity due to changes in generator ability to exercise market power have little impact on the overall conclusions of Chapters 5 and 6.

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[3] 12% is from Bushnell and Saravia [13].

[4] 3% comes from applying Mansur's factor of four to the 12% Bushnell and Saravia estimate.

[5] As discussed in Chapter Three.

## Transmission and Distribution Constraints

A fourth simplification is in my treatment of the ISO-NE energy market as a single node. In reality, ISO-NE takes into account transmission constraints and line losses, and different clearing prices are calculated for each node in the network[6]. By treating the entire market as a single node, I implicitly assume that transmission constraints are zero and T&D costs are constant. Because I aim to develop a general idea of how renewable generators will fare under RTP, such a simplification is appropriate. An investment-grade analysis for a particular location, however, would require some accounting for the relevant transmission constraints. This simplification is consistent with the assumptions made in other models of power markets, including those discussed in Chapter 3 [10, 21].

## Scope of Consumer Response

Additionally, I assume that there is no inter-hour substitution of electricity use, and that there is no technological change that alters the demand elasticity. While these two considerations are essential in long-run models that include the possibility of innovations like thermal energy storage or smart appliances, in the short-run considered with this model they are not likely to play a role.

This simplification is consistent with other models of RTP [10, 21]. It is also consistent with both revealed and stated behavior in real trials of RTP. As discussed above, estimates of cross-price elasticity in the Duke Power RTP study [41] are at least one order of magnitude smaller than own-price elasticity estimates, supporting the hypothesis that substitution and peak-shifting are not the most important aspects of consumer price response. A survey of Niagara Mohawk Power Corporation's industrial customers on RTP also lends qualitative support for this hypothesis [23]. 28% of the survey respondents indicated that they do not respond to prices, and of the 71% who do respond only 17% indicated that demand shifting was their primary means of price response. The other respondents choose to either forego use in high-price hours or use on-site generation during those hours. The survey results are summarized in Table 4.1. The addition of endogenous elasticity or intra-hour

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[6] This is known as Locational Marginal Pricing and is discussed elsewhere, including in Stoft [40]

substitution *is* a possible extension of the model, but based on this evidence the assumption of no substitution seems justified in the short-run.

Table 4.1: Stated Price-Response Strategies of Niagara Mohawk RTP Customers

| Strategy | % of Respondents |
|---:|:---:|
| Don't Respond | 28% |
| Forego | 33% |
| Shift | 17% |
| Onsite Generation | 9% |
| Forego & Onsite Gen. | 7% |
| Forego & Shift | 5% |

*Data summarizes results from Hopper [23].*

## Summary of Key Assumptions

In summary, the key assumptions that define the scope of the model are:

1. Restriction to the day-ahead energy market
2. Exclusion of non-energy components of the day-ahead bid
3. No treatment of the effect of demand elasticity on gaming
4. No treatment of transmission constraints
5. No inter-hour substitution
6. No technological change in the short-run

Assumptions 1 and 2 define the model boundary. Assumptions 3 and 4 amount to the assumption that producer and system operator behavior is exogenous. Assumptions 5 and 6 define the scope of consumer behavior.

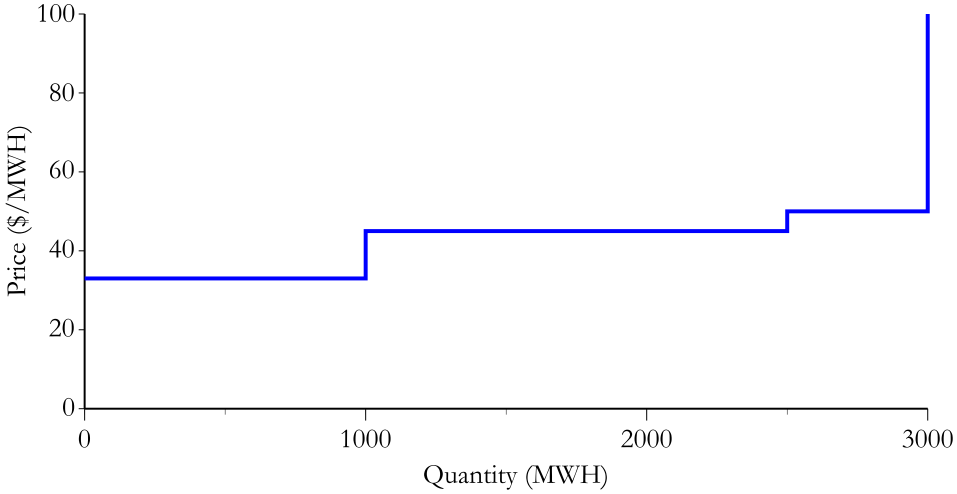
## 4.3 Model Formulation

With these assumptions, we can develop a simple equilibrium market model for each hour and use comparative statics to find new clearing prices and quantities. For each hour, the supply curve is determined by the marginal costs of each plant in the network, which are revealed in their bids to the day-ahead market[7]. For example, if three plants submit the bids shown in Table 4.2, the supply curve defined by those bids is the one shown in Figure 4-1.

Table 4.2: Example Bids

| Bid Quantity (MW) | Price ($/MWh) |
|---|---|
| 1000 | 33 |
| 1500 | 45 |
| 500 | 50 |

Figure 4-1: Supply Curve Defined by Bids in Table 4.2



Individual bids are much smaller than aggregate demand, though, so we can picture the supply curve as smooth in the aggregate. This is shown in Figure 4-2.

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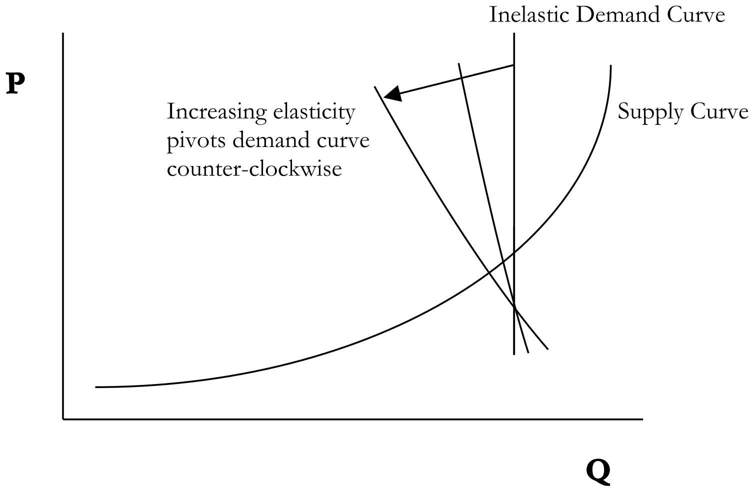
[7] Bids reveal marginal cost if we assume either 1) firms do not exercise market power or 2) the generation oligopoly is engaged in Bertrand competition (i.e. interaction among non-coordinating oligopolists who compete by setting price). This model of firm behavior is shown to set prices at competitive levels. This assumption is discussed in Section 4.2.3, and sensitivity to this assumption is explored in Appendix C

Figure 4-2: Smooth Supply Curve with Inelastic and Elastic Demand



The wholesale demand for each hour is dependent only on the flat retail price and the latent[8] demand in that particular hour. Since it is inelastic with respect to the real price of power during the hour, it is depicted as a vertical line in Figure 4-2. The intersection of this line with the supply curve defines the clearing price and quantity for the flat retail pricing scenario. All energy sold trades at this clearing price, so the total payments from consumers to producers is simply $\bar{P}_t * \bar{Q}_t$. For generator $x$, who sold quantity $q_{xt}$, revenues are $q_{xt} * \bar{P}_t$.

Real-time pricing adds elasticity to the demand curve, changing the slope as shown in Figure 4-2. This shifts the wholesale market equilibrium to $(P^{RTP}, Q^{RTP})$ and changes the total payments as shown in Figure 4-3. Generator $x$'s revenues are now $q'_{xt} * P'_t$. Unless generator $X$ was a marginal unit under the flat pricing scenario, $q'_{xt} = q_{xt}$.

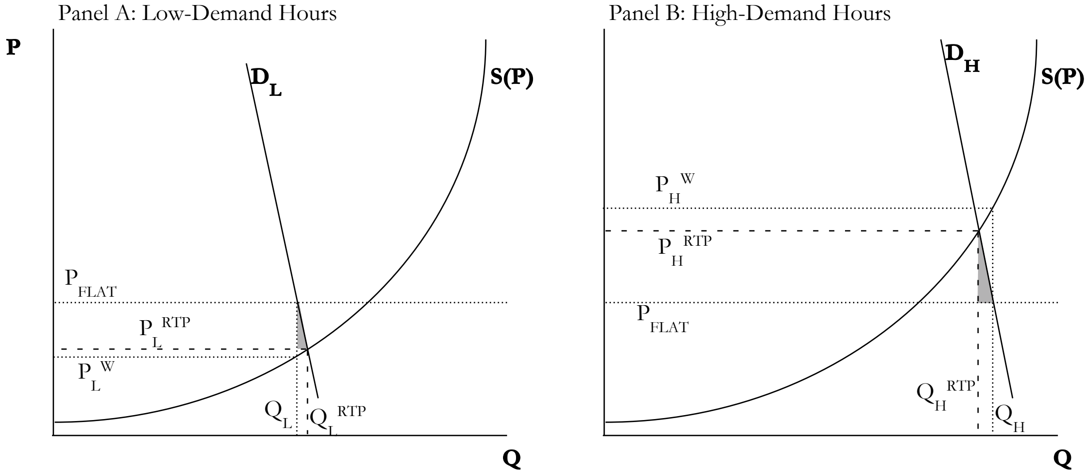
While the supply curve is defined by the bids submitted to the day-ahead market, there is no equivalent mechanism which reveals the shape of the demand curve, and we must therefore make some assumption about the functional form of the curve. Following previous models [10, 21], I use a constant elasticity demand curve

$$D_t = A_t * P(D_t)^{\epsilon} \tag{4.1}$$

---

[8] Throughout the thesis, I use "latent" demand to refer to the magnitude of non-price shocks in demand. In other words, the latent demand is the demand schedule with respect to price, given the state of temperature, time of day, day of week, time of year, etc. during that model period.

Figure 4-3: New Equilibria with RTP in Low- and High-Demand Hours


Panel A: Low-Demand Hours

Panel B: High-Demand Hours

The advantages of this form over alternative forms include its analytic convenience, its use in much of the RTP literature, and the large number of econometric studies which have estimated an elasticity using this form. In this research I consider scenarios with 100% of customers on RTP, but in Appendix C I show that relaxing this assumption is not expected to alter any qualitative results.

## 4.4 Solution Algorithm

The model itself is scripted in PERL (the code is included in Appendix B), while the data driving the model is stored in a relational database as described in the next section and Appendix A. The inputs for each hour include all bids submitted to the day-ahead market, observed demand $Q_{obs}$, observed flat retail price, non-generation costs, and own-price elasticity of demand. Given these inputs, the algorithm for each hour is as follows:

1. Sort supply bids by price per unit power, increasing. To each bid price, add the flat non-generation cost input. This represents the non-generation costs which end-users face, including transmission, distribution, and capital cost recovery.

2. For each bid $i$, calculate the cumulative power $Q_i$ as the sum of all power bid in to the market at less than or equal to the bid price $P_i$. The supply curve is then defined by

the points $(Q_i, P_i)$ for all $i$.

3. Find the lowest price at which $Q_i \geq Q_{obs}$. This is the equilibrium price under flat retail pricing, $\bar{P}^*$.

4. Using the observed load $Q_{obs}$, observed flat retail price $\bar{P}_{obs}$, and elasticity $\epsilon$, calculate the hourly demand factor $A_t$ as

$$A_t = Q_{obs}/(\bar{P}_{obs})^{\epsilon} \tag{4.2}$$

The demand curve is then defined as

$$Q_t = A_t * P^{\epsilon}. \tag{4.3}$$

5. Find the intersection of the supply and demand curves. This defines the RTP equilibrium $(P_t^*, Q_t^*)$.

These steps are shown in Figure 4-4.

## 4.5 Input Data

The following section describes the sources, manipulation, and calibration of the input data used in the market model. Bids, demand, retail price, and market segmentation data are stored in a relational database, the structure of which is fully documented in Appendix A. Compilation of this data set was one of the most time-consuming aspects of this research, with 60 million bid records and price and resource data from a variety of sources.

### Bids Database

A complete set of all bids submitted to the day-ahead energy market for every hour since the restructured market began in 1998 was compiled from data from ISO-NE[9] [17]. Each unit

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[9] I wrote the script in Appendix B to read the individual daily bid files available from ISO-NE into single table for import into a MySQL database.

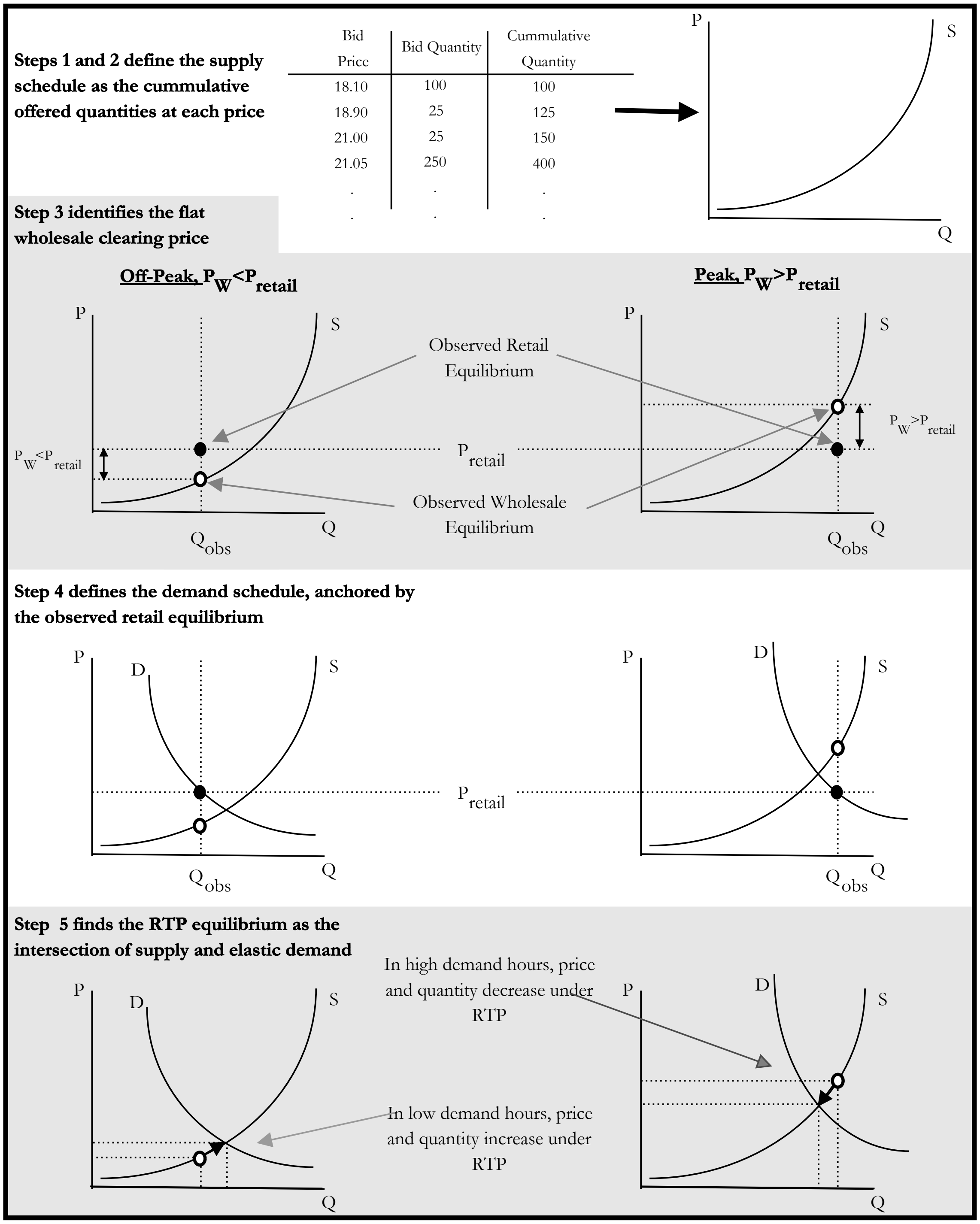


Figure 4-4: Steps of Market Simulation Algorithm

| Bid Price | Bid Quantity | Cummulative Quantity |
|---|---|---|
| 18.10 | 100 | 100 |
| 18.90 | 25 | 125 |
| 21.00 | 25 | 150 |
| 21.05 | 250 | 400 |
| . | . | . |
| . | . | . |

submits a multi-part bid, containing non-energy costs (startup, ramping, etc) and up to ten sequential energy blocks. For example, a plant with increasing marginal costs can offer 50 MWh at \$25/MWh but require \$30/MWh to produce another 10 MWh. Over the period for which data was available (1998-2006), 18 million complete bids were submitted. Each bid contained an average of slightly over 3 parts per bid, for a total of 60 million individual energy offers. Units are identified only with a masked ID number which is consistent across hours - there is no location or fuel-type information available in the bid dataset. Because I am only interested in the market equilibrium and not the production of particular units, I treat each offer as an individual bid in the algorithm above.

Figure 4-5 shows an example supply curve, defined by the bids submitted to ISO-NE for the 4PM hour on 31 July 2003. Table 4.3 reports summary statistics for the energy bids submitted to the ISO-NE day ahead market. Note that before mid-2003, market rules allowed bidding negative price in order to deal with cost non-convexities (start-up and shut-down costs), while rule changes in 2003 removed the necessity to bid negative prices by allowing generators to reveal those costs in a separate component of their bid. Note also that the maximum bid price was set by a price cap which changed in 2003.

Figure 4-5: Typical ISO-NE Supply Schedule - 5 to 6 PM August 6, 2006

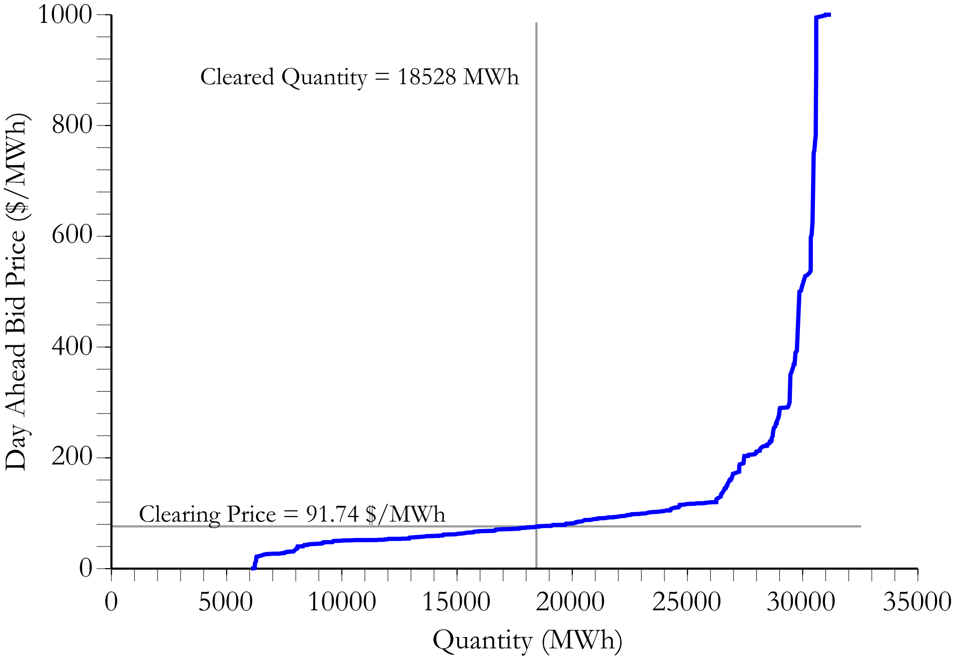


Table 4.3: Summary Statistics: Bids Submitted to ISO-NE Day Ahead Market

| Year | Number of Bids | Min Bid Price ($/MWh) | Max Bid Price ($/MWh) |
|---|---|---|---|
| 1999 | 4,010,418 | -11 | 10000 |
| 2000 | 7,651,389 | -1500 | 10000 |
| 2001 | 9,012,177 | -1000 | 16640 |
| 2002 | 9,438,726 | -1000 | 10000 |
| 2003 | 8,731,859 | -999 | 1000 |
| 2004 | 8,686,034 | 0 | 1000 |
| 2005 | 6,862,403 | 0 | 1000 |
| 2006 | 5,983,982 | 0 | 1000 |

*In March 2003 ISO-NE modified its market design (to what is called the Standard Market Design). This change eliminated the need for negative bidding and lowered the price cap - hence the abrupt change in values after 2003.*

## Demand Time Series

ISO-NE reports the metered system load for each hour since 1998 and the quantities cleared in the day-ahead and spot markets for each hour since market rules were changed in 2003 [18]. For consistency with the assumptions of this model, I use day-ahead cleared quantity as the observed demand input to the algorithm above. Figure 4-6 shows the observed demand over a typical month (June 2005). Figure 4-7 shows the high and low hourly demand for each day from 2003 to 2006 (starting with the change in market rules in March 2003).

Figure 4-6: Hourly Demand Cleared in Day-Ahead Market, June 2005

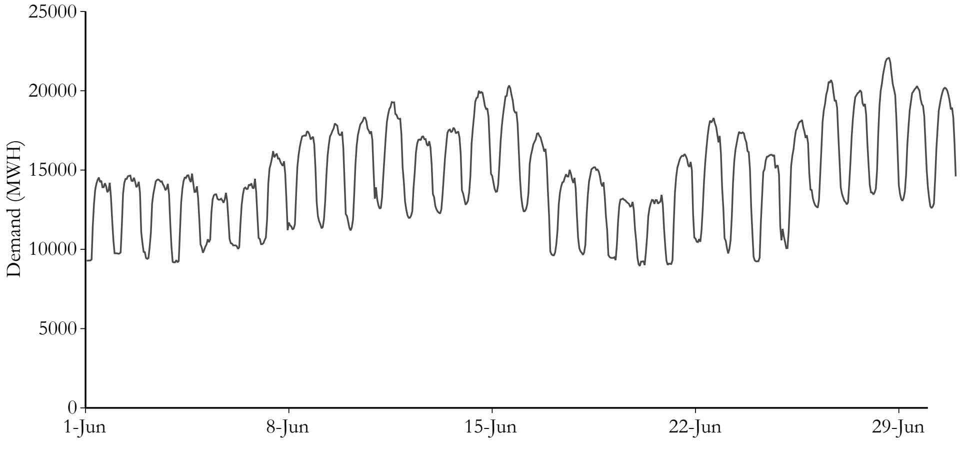
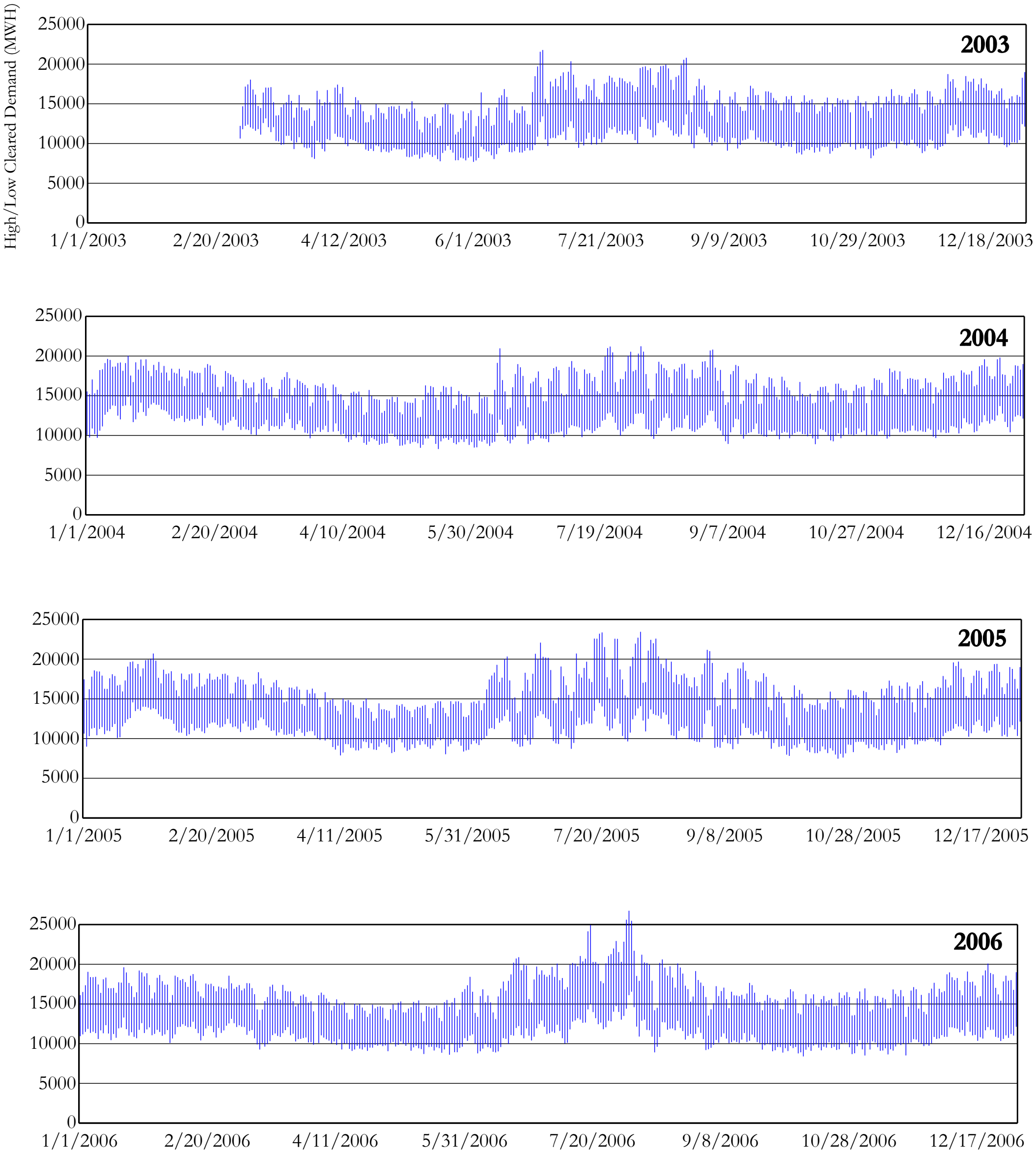


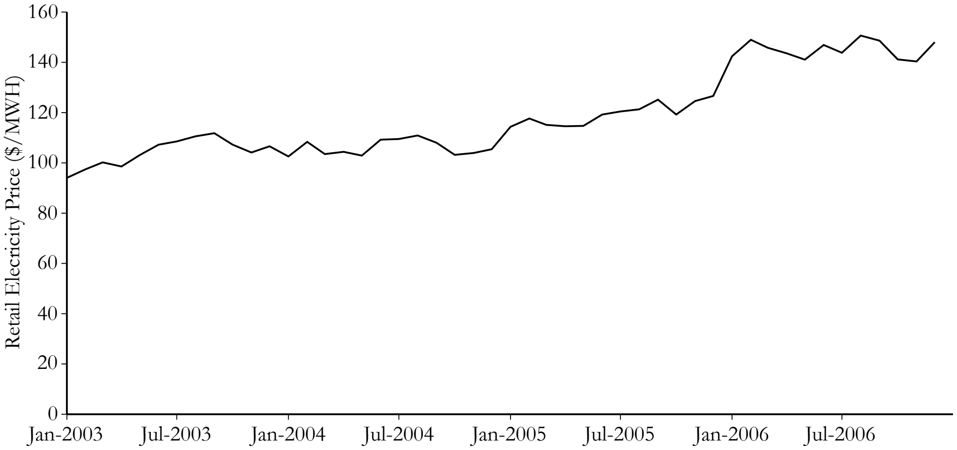
Figure 4-7: High and Low Hourly Demand (Cleared in Day-Ahead Market) for Each Day, 2003-2006



## Retail Price Time Series

The Energy Information Administration reports monthly average retail electricity rates by state from 1990 to the present [34]. For input to the model, I used the average retail rate from the five New England states, weighted by total electricity sales in those states. Figure 4-8 shows the average retail rate over the model period.

Figure 4-8: Average New England Retail Electricity Price, 2003-2006



## Non-generation Costs

Non-generation costs (NGC) account for approximately half of the end-user's electricity bill. These costs include transmission, distribution, and the recovery of stranded costs (i.e. non-competitive investments made by utilities before restructuring). Non-generation costs vary significantly from region to region and among users. Instead of capturing this heterogeneity I follow the studies cited in Chapter Three [10, 21] and use a single non-generation cost for all users. The model was run with non-generation costs ranging from $45—$100/MWh and the resulting market clearing prices were compared to those reported by ISO-NE. Selecting a non-generation cost of $65 for the period of 2003-2005 and $95 for the 2006 year delivered the best fit to historical data. The results shown in Section 4.6 use this T&D cost input.

Sensitivity tests in Appendix C explore the consequences of this choice. In general, the results are qualitatively robust across the range of $50-$100/MWh. Given these robust results, significant effort was not made to calibrate the NGC in more detail. The jump to \$95/MWh in 2006 was used in order to obtain a consistent consumer response across years, since a flat rate of \$65/MWh resulted in increased consumption in 2006 due to RTP (whereas 2003-2005 have decreases). Since I am unaware of significant structural changes in the power system or population between 2005 and 2006, this discontinuity in consumer response seems undesirable and the larger NGC cost was used in 2006 to achieve a demand response more similar to other years. T&D costs may have been constant or slowly rising over the model period, so the jump in NGC must come from elsewhere. I speculate that the jump represents how the non-T&D components of NGC changed in response to Hurricane Katrina and speculation in natural gas in the second half of 2005.

Specifically, the NGC in this model represents not just T&D but also any other differences between the day-ahead wholesale market and the retail market. Since significant amounts of power are traded in periods besides the day-ahead market, the NGC includes a balancing factor between prices in the day-ahead and other markets - in particular, the prices paid in long-term bilateral contracts. While I do not have data on the trading price of these contracts, it is possible that long-term rates increased significantly after the Fall of 2005, when both Hurricane Katrina and significant speculation in futures markets drove up the cost and volatility of gas, which could translate to large increases in long-term forward electricity contract prices. As a consequence, the NGC in this model, which represents all differences between the day-ahead wholesale market and the retail market, would jump after Fall 2005. This hypothesis is laid out in Figure 4-9. The upper series (blue) shows the average retail price of electricity for all consumers, by month, which is the retail price input to the model. The lower series (red) shows the average retail cost *minus* the quantity-weighted average wholesale price[10]. This difference is the monthly average of what the NGC represents. As I note in the figure, late-2005 shows a sudden drop in this difference, caused by a spike in wholesale prices brought on by Katrina and gas speculation. In 2006, the market seems to

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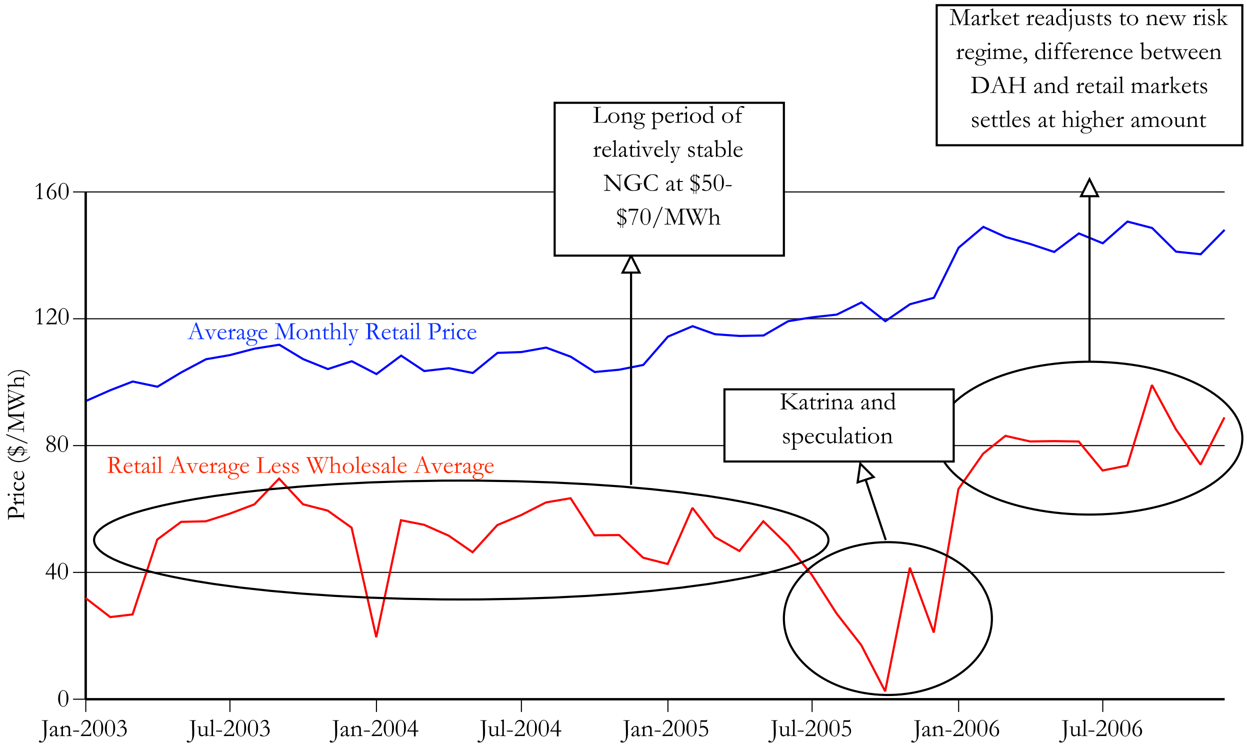
[10] The average wholesale cost in month m is calculated as

$$\bar{C}_m = \frac{\sum\limits_{t\in m} P_t Q_t}{\sum\limits_{t\in m} Q_t} \tag{4.4}$$

The difference plotted is simply the average retail price minus this quantity.

readjust to new, higher, NGC. While this series is too limited to detect stable trends, it should provide some support for the NGC's used in the base run. Empirical examination of this effect should be done in future work, but for the purposes of this thesis the imprecise calibration of NGC should not be cause for concern due to the robustness of results across a wide range of values.

Figure 4-9: Average Retail and Wholesale Prices, with NGC Hypothesis



## Elasticities

A large number of studies have used econometric methods to estimate the own-price elasticity of demand for electricity, with significant variation in the results. Dahl [15] presents a meta-survey of about 30 econometric studies which estimate elasticity using the constant-elasticity (or log-log) functional form, presenting the range of elasticities reported in each. Rather than choose one, I tested numbers across the range of short-run elasticities reported in Dahl (roughly -0.1 to -0.5) to estimate the sensitivity of my results to the demand elasticity. This approach is consistent with other recent RTP models including Borenstein and Holland's long-run model [10] and Holland and Mansur's short-run model [21].

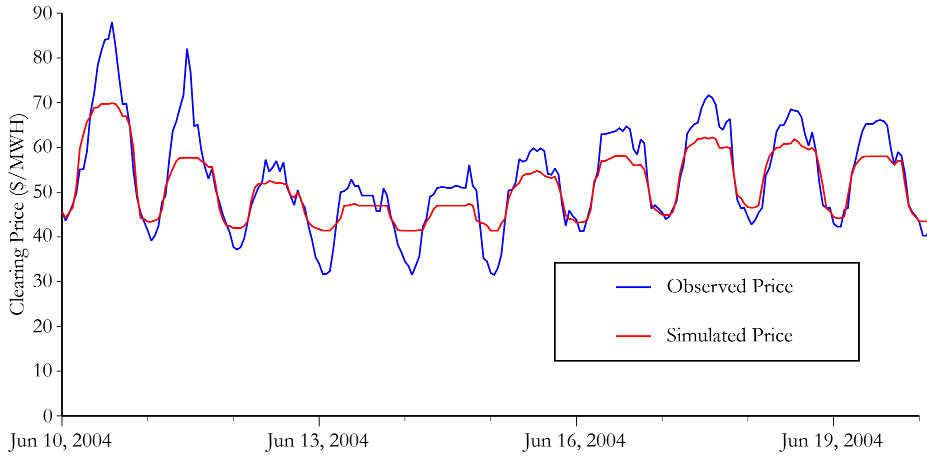
## 4.6 Market-Level Results — Load, Price, and Sector Revenues

In this section I present the results of model runs using 2003-2006 input data described above and demand elasticities of 0.1, 0.3, and 0.5. Sensitivity to NGC- and load-perturbations, as well as changes in non-competitive behavior, was tested and the results of these runs are included in Appendix C.

### Simulation of the Flat-Tariff Scenario

Before discussing the RTP simulation, I compare my simulation of the wholesale market under flat retail pricing with the historical wholesale market prices. Figure 4-10 compares my *simulated wholesale clearing prices* in the flat-rate scenario with the *real market clearing prices* reported by ISO-NE. Two observations are important. First, the two series are highly correlated (with $R^2 = .836$), and second, the simulated result is less volatile than the historical price series (with a standard deviation of 20.3 for the *simulated flat-tariff* prices versus 23.9 for the *historical flat-tariff prices*). This difference in volatility is expected based on the assumptions made above. Transmission constraints, cost non-convexities, and market power are all expected to increase volatility. These assumptions, however, are consistent with other models of RTP and give the model a level of detail which is most appropriate for the task at hand - identifying, in a broad sense, how RTP differentially effects renewable generators. My results can be interpreted as a conservative estimate of consumer price response, since increased volatility (higher high prices and lower low prices) would increase the magnitude of the response.

Figure 4-10: Comparison of Historical and Simulated Wholesale Clearing Prices, Both With Flat Retail Pricing, Jun 10-20, 2004



## Real-Time Pricing Scenarios

Three primary RTP scenarios are discussed in this section - using elasticities of -0.1, -0.3, and -0.5, with all else equal. The baseline scenario that each is compared to is the simulated flat-tariff scenario (not the historical prices). Table 4.4 summarizes the market-level response for all scenarios. Increasing elasticities are shown to decrease the average hourly quantity and price and compress the range of hourly quantities and prices. Figure 4-11 compares quantity changes and sector-wide revenue changes for each scenario, showing that the magnitude of revenue changes are much larger than changes in demand.

Figure 4-11: Comparison of Total System Quantity and Revenue Under RTP

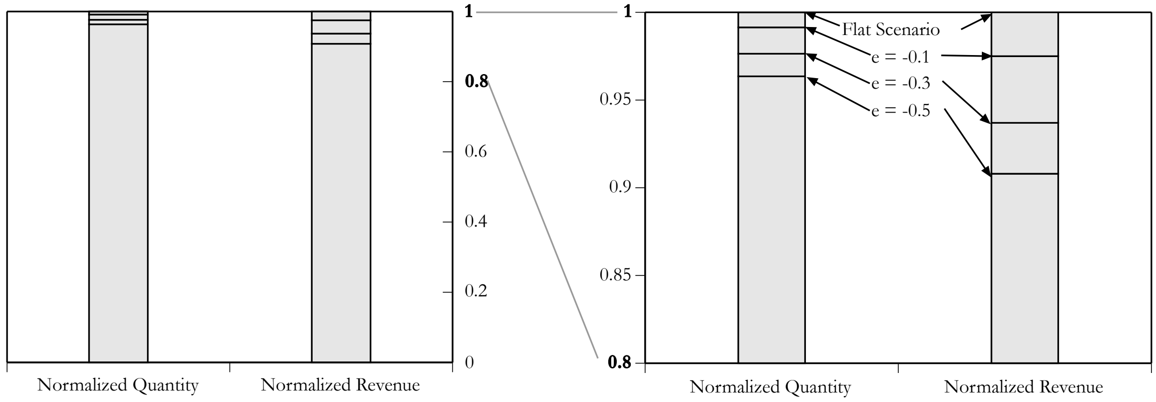


Table 4.4: Summary of Hourly Quantity and Price Responses to Real-Time Pricing

| Panel A: Comparing Hourly Quantities (MWh) | | | | |
|---|---|---|---|---|
| Tariff | Mean | Median | Max | Min |
| Flat | 13980 | 14020 | 26740 | 7470 |
| $\epsilon$ = -0.1 | 13860 | 13920 | 25620 | 7650 |
| $\epsilon$ = -0.3 | 13650 | 13710 | 24080 | 7800 |
| $\epsilon$ = -0.5 | 13470 | 13520 | 22920 | 7960 |
| **Panel B: Comparing Hourly Wholesale Prices ($/MWh)** | | | | |
| Tariff | Mean | Median | Max | Min |
| Flat - Observed | $61.34 | $56.04 | $529.21 | $2.99 |
| Flat - Simulated | $57.48 | $53.37 | $373.25 | $19.98 |
| $\epsilon$ = -0.1 | $56.86 | $53.00 | $261.89 | $19.98 |
| $\epsilon$ = -0.3 | $55.92 | $52.55 | $170.80 | $20.11 |
| $\epsilon$ = -0.5 | $55.17 | $52.00 | $140.00 | $20.66 |

Figures 4-12, 4-13, and 4-14, show these effects in more detail for elasticities of -0.1, -0.3, and -0.5, respectively. In each of these figures, the distribution of hourly prices and quantities is shown for the flat-tariff scenario in black, and for the RTP scenario in blue. Panels (a) and (b) show the distribution of price and quantity, respectively, while panels (c) and (d) report the cumulative distributions. All RTP scenarios compress the distributions of hourly prices and quantities relative to the flat tariff, with increasing compression at higher elasticities.

Figure 4-15 shows how the price changes simulated by the model occur throughout the year. Each figure is a 24x12 plot, showing the average change in clearing price for each hour of the day (1-24) and each month of the year. Specifically, each point shown is calculated as

$$\Delta P_{month=m,hour=h} = average((P^{RTP}_{m,h} - P^{flat}_{m,h})/P^{flat}_{m,h}) \tag{4.5}$$

Examination of these figures reveals some seasonal patterns of price change. Specifically, prices fall January mid-day (most significantly in 2003 and 2004 - prices were particularly high during those periods due to high natural gas prices) and during summer days, while prices increase overnight, particularly during the fall.

In this simple model, generator revenues are equal to the sum across all periods of the

Figure 4-12: Load and Price Frequency Distributions with $\epsilon = -0.1$

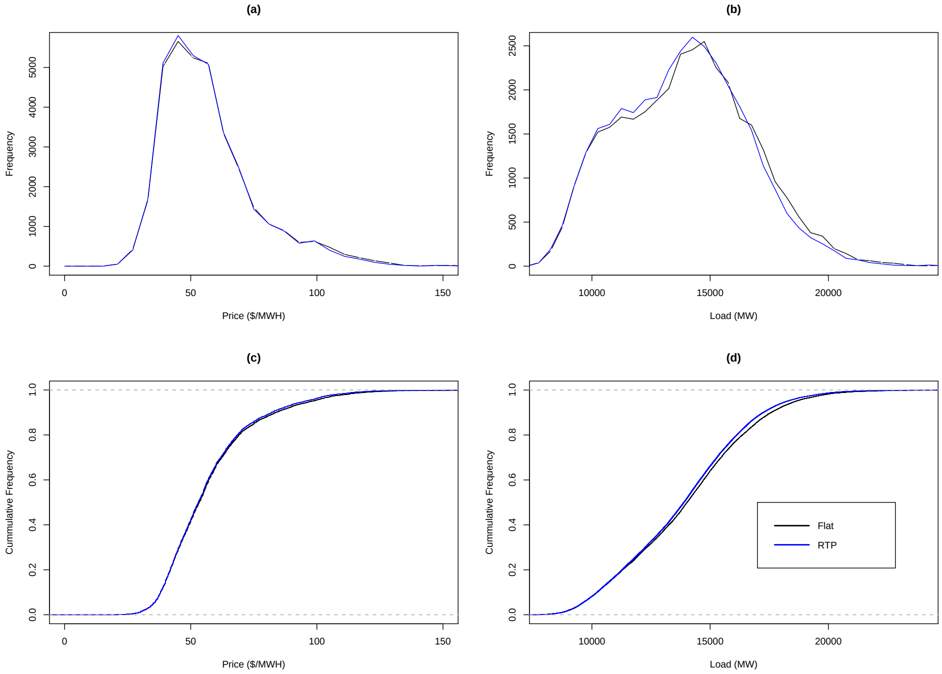


Figure 4-13: Load and Price Frequency Distributions with $\epsilon = -0.3$

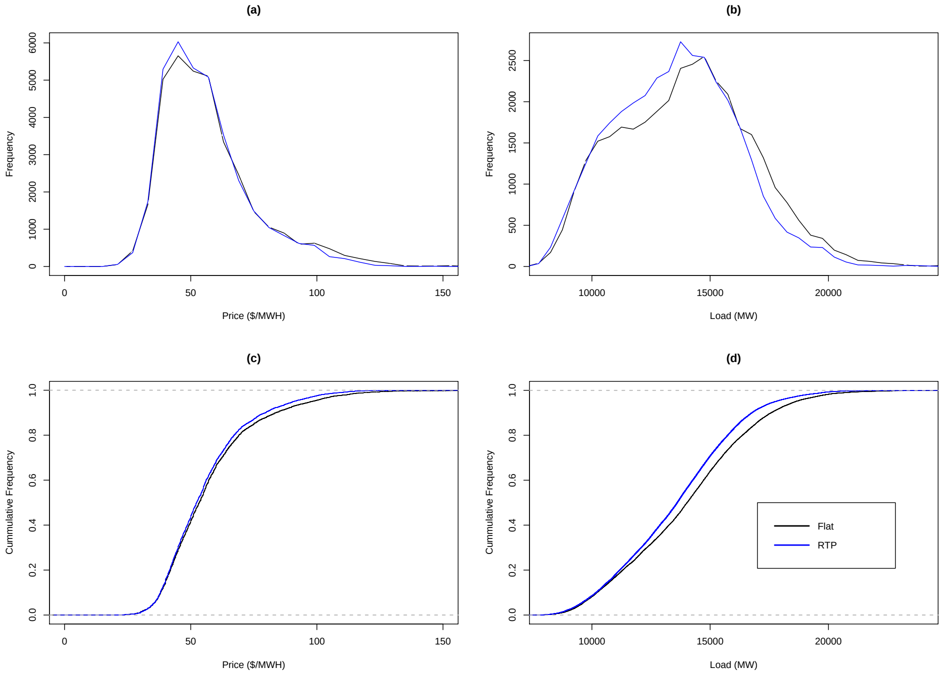


Figure 4-14: Load and Price Frequency Distributions with $\epsilon = -0.5$

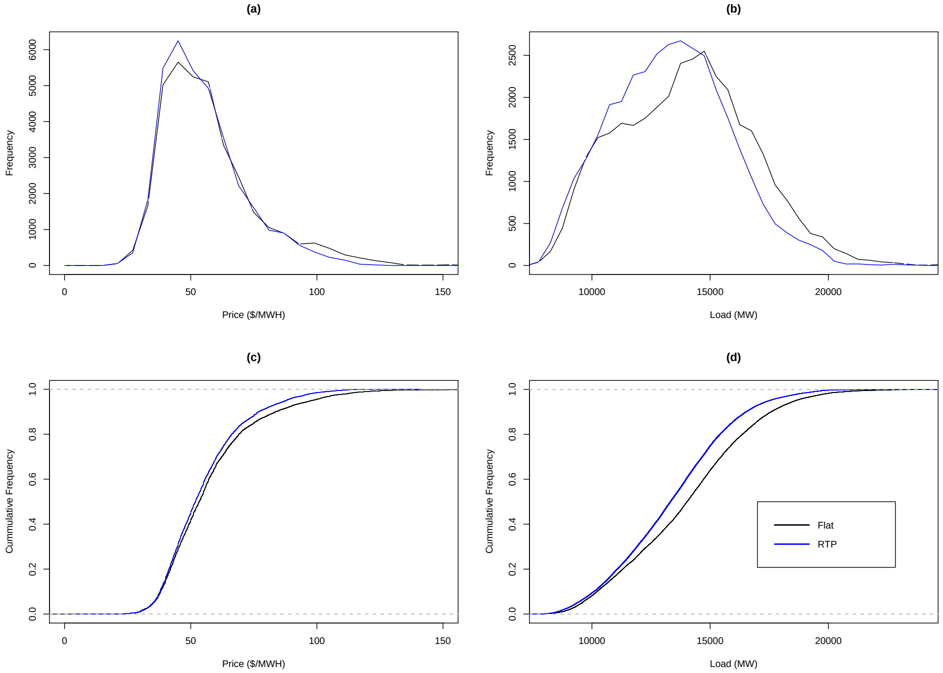
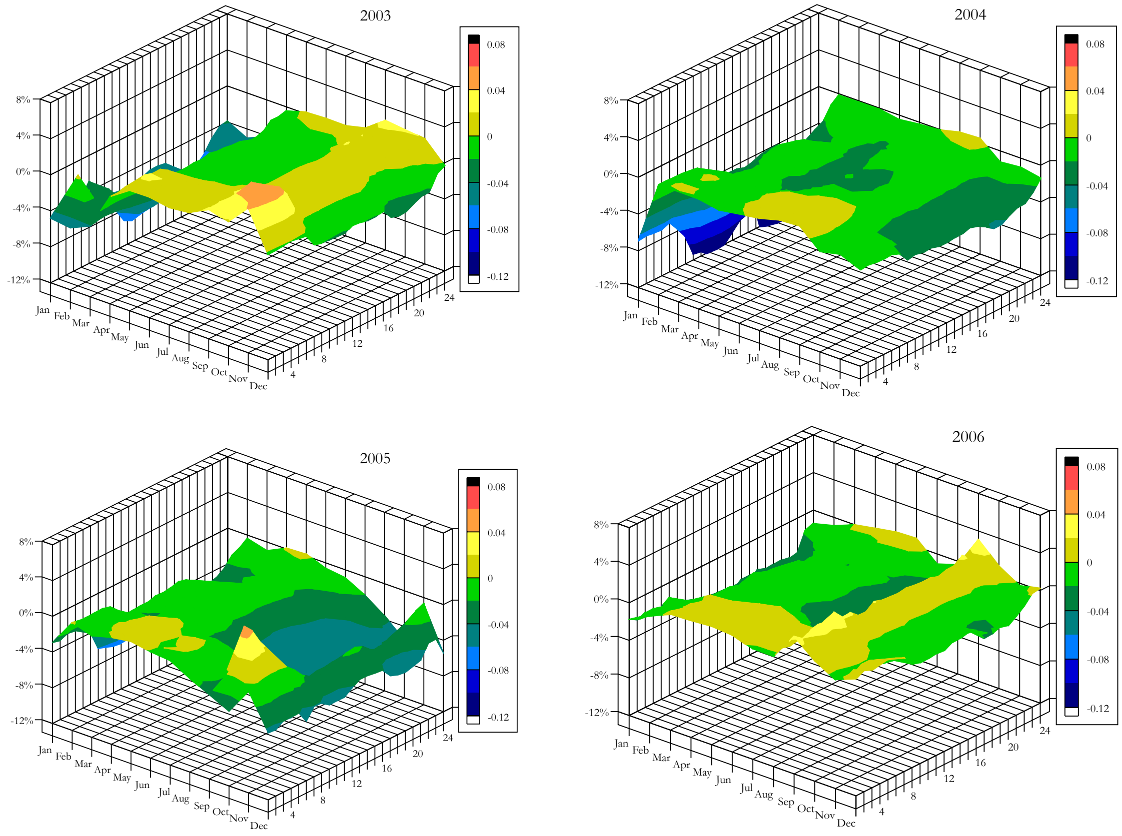


Figure 4-15: Average Hourly Price Change By Month and Year, $\epsilon = -0.3$



product $P^* * Q^*$. These payments are summarized in Table 4.5. Across all years and with all elasticities, RTP leads to lower total payments to generators, with greater losses at higher price elasticities.

Table 4.5: Summary of Producer Revenues ($B) Under Real-Time Pricing

| | | Scenario | | | |
|---|---|---|---|---|---|
| | | | RTP Elasticity | | |
| Year | | Flat Tariff | $\epsilon = -0.1$ | $\epsilon = -0.3$ | $\epsilon = -0.5$ |
| 2003 | Revenue | $5.57 | $5.48 | $5.32 | $5.21 |
| | Change from flat tariff | | -1.7% | -4.5% | -6.6% |
| 2004 | Revenue | $6.71 | $6.50 | $6.23 | $6.02 |
| | Change from flat tariff | | -3.0% | -7.2% | -10.2% |
| 2005 | Revenue | $9.34 | $9.04 | $8.55 | $8.17 |
| | Change from flat tariff | | -3.3% | -8.5% | -12.6% |
| 2006 | Revenue | $7.40 | $7.28 | $7.10 | $6.96 |
| | Change from flat tariff | | -1.5% | -4.0% | -6.0% |
| All | Revenue | $29.02 | $28.30 | $27.20 | $26.36 |
| | Change from flat tariff | | -2.5% | -6.3% | -9.2% |

The time series presented in Figures 4-16 and 4-17 show the model results in detail for an example week in February and October of 2005, respectively. In this hour-by-hour look, the smoothing effects of RTP on system load, and the implications for producer revenues, are clear. In the next chapter I will examine how these system responses translate into losses or gains at the level of individual generators, and in particular how the timing of the system response aligns with the availability of renewable resources.

Figure 4-16: Hourly Load, Price, and Revenue - Feb 13-21, 2005

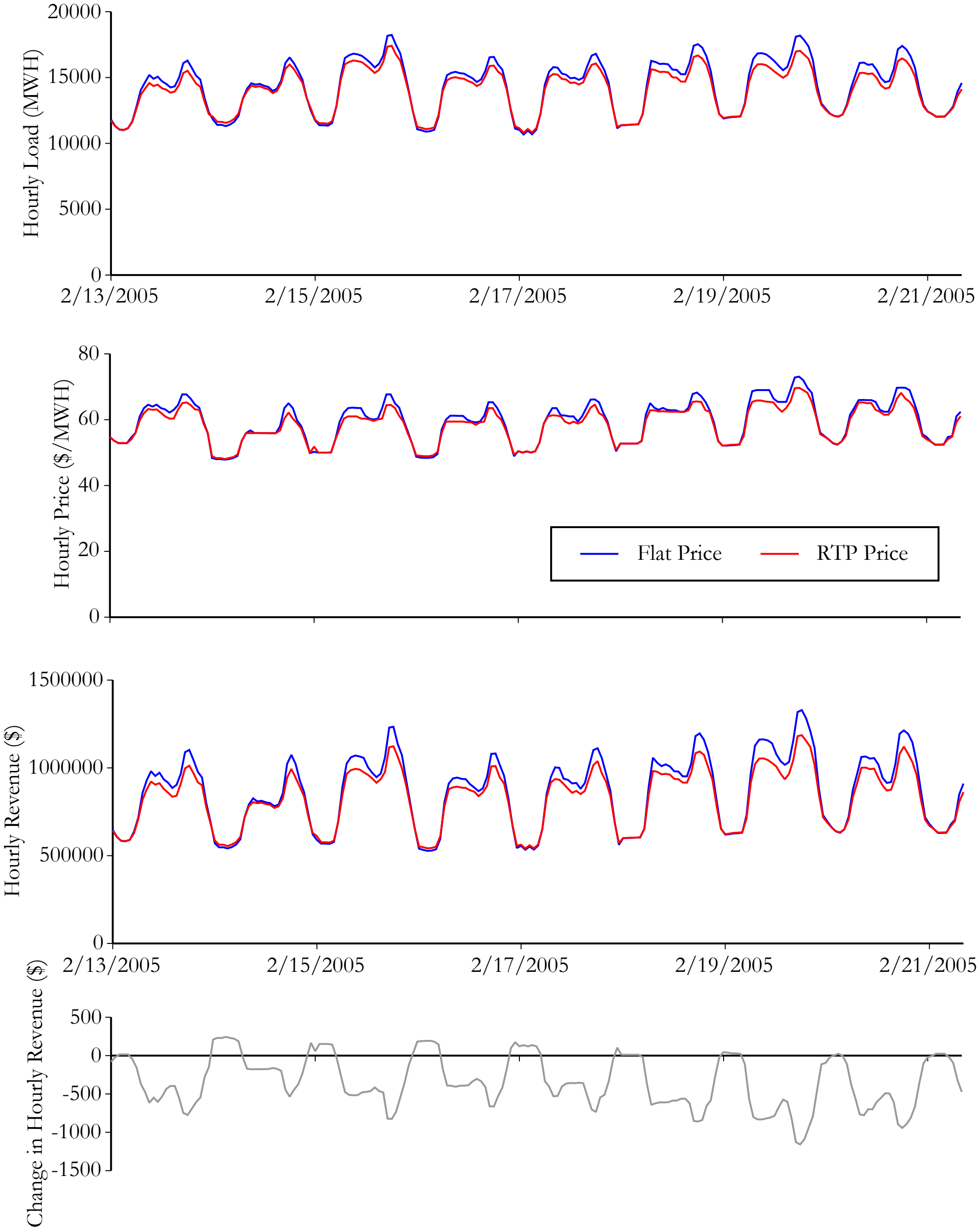
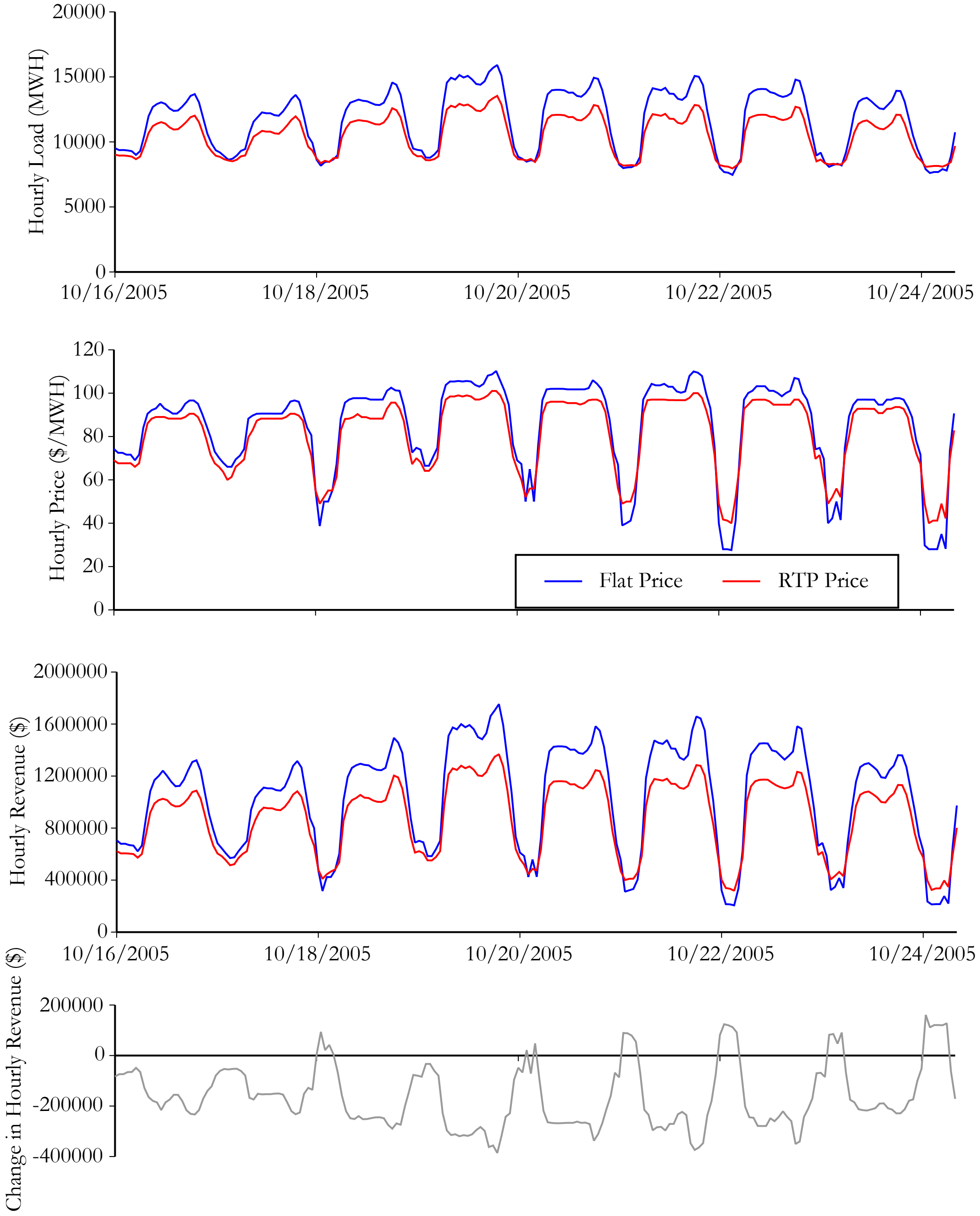


Figure 4-17: Hourly Load, Price, and Revenue - Oct 16-24, 2005



# Chapter 5

# Generator Revenues Under Real-Time Pricing

## 5.1 Introduction

With the modeled wholesale market response to RTP, we can use the changes in clearing prices and information about an individual unit's generation to calculate that unit's expected change in revenues. First I will consider the case of intermittent renewable generation, such as wind and solar photovoltaics. The analysis takes into account the time-dynamic of renewable resource availability and uses real resource data from three locations in New England and simulated resource data based on typical weather to develop an idea of how renewable generators will fare under RTP, relative to the generation sector as a whole. As discussed in the Chapter One, this analysis represents a novel contribution to the study of RTP, as no previous work has investigated the effects of RTP on intermittent generators specifically. I find that, while renewable generators do indeed lose revenue under RTP, these losses are smaller than those expected by the generation sector as a whole. For a moderate elasticity of -0.3, the renewable generators I analyze expect revenue losses of 2-4%, compared with 6% losses for the generation sector as a whole. RTP, then, is not expected to differentially disadvantage solar and wind generators in the cases I examine.

Next, I take a simplified approach to determining the revenue change for fossil generators. While the case of RTP and fossil generators' has been studied elsewhere in more detail [21], I show a high-level analysis of fossil generators' revenues in order to provide some context for the renewable generators' revenue changes and to inform the discussion of political factors behind RTP adoption in Chapter 7. As expected, I find that those units who are only dispatched in the highest demand hours (i.e. peak generators with high marginal costs) expect significant revenue loss compared to average generators (a 70% loss in the high-elasticity scenario).

## 5.2 Intermittent Generator Methodology

Renewable generators typically have marginal operating costs of close to zero, so they will bid any available power into the wholesale market at zero price[1]. In this respect these generators are price-takers — they are always dispatched, and they are paid the wholesale clearing price for anything they have available. The renewable generator's revenues are therefore the sum over all hours of the wholesale price times the available generation, which itself depends on the time-dynamic of wind or solar availability at the particular generation site.

$$R_i = \sum_{t=1}^{T} P_t * G_{t,i} \tag{5.1}$$

where

$$\begin{aligned} R &= Revenue \\ P &= WholesalePrice \\ G &= Generation \\ i &= Generation\,Unit\,of\,Interest \\ t &= hour \end{aligned}$$

---

[1] Assuming that the generator sells in to the wholesale market. An alternative arrangement — the use of long-term contracting — would dampen the effects of RTP on revenue to exactly the extent that long-term prices are insulated from the wholesale market.

## 5.3 Intermittent Generator Data

Three example generators were analyzed, representing three very different availability regimes — near-shore wind, far off-shore wind, and solar photovoltaic generation. Example sites were selected based on data availability and caution warns against extrapolating these results to all generators of a certain class or across the region. Having modeled the market response to RTP, it is relatively straightforward to reanalyze particular sites in the future rather than extrapolating these results. The three intermittent generator datasets are described below.

In addition to the *in situ* solar data, simulated solar output based on typical meteorological conditions was analyzed in order to supplement the relatively sparse solar data. This exercise is discussed after the analysis of *in situ* data.

### Hull Near-Shore Wind

Hull, MA is a coastal community southeast of Boston with a municipal power company that is currently studying the possibility of expanding its existing wind generation capacity. As part of this effort, a team of researchers from the University of Massachusetts and MIT have developed a historical hourly wind resource dataset[2]. Hourly wind speeds were measured at Hull in 2006 and the Measure-Correlate-Predict method [38] was used with a historical dataset from nearby Logan Airport in order to synthesize an extended historical dataset. Wind speeds were scaled to hub-height using a power law and converted to generation output using published power curves for the General Electric 3.6 MW turbine[3]. Average wind speeds and generation output are shown by hour and month in Figure 5-1.

### Nantucket Far Offshore Wind

Data from the NOAA observation buoy at Nantucket is included as an example of a far offshore wind resource [31]. As the hourly dataset was complete (i.e. no gaps existed) for the period to be considered, no MCP was used. Wind speed was scaled to hub-height using a power law and converted to generation output using published power curves for the General

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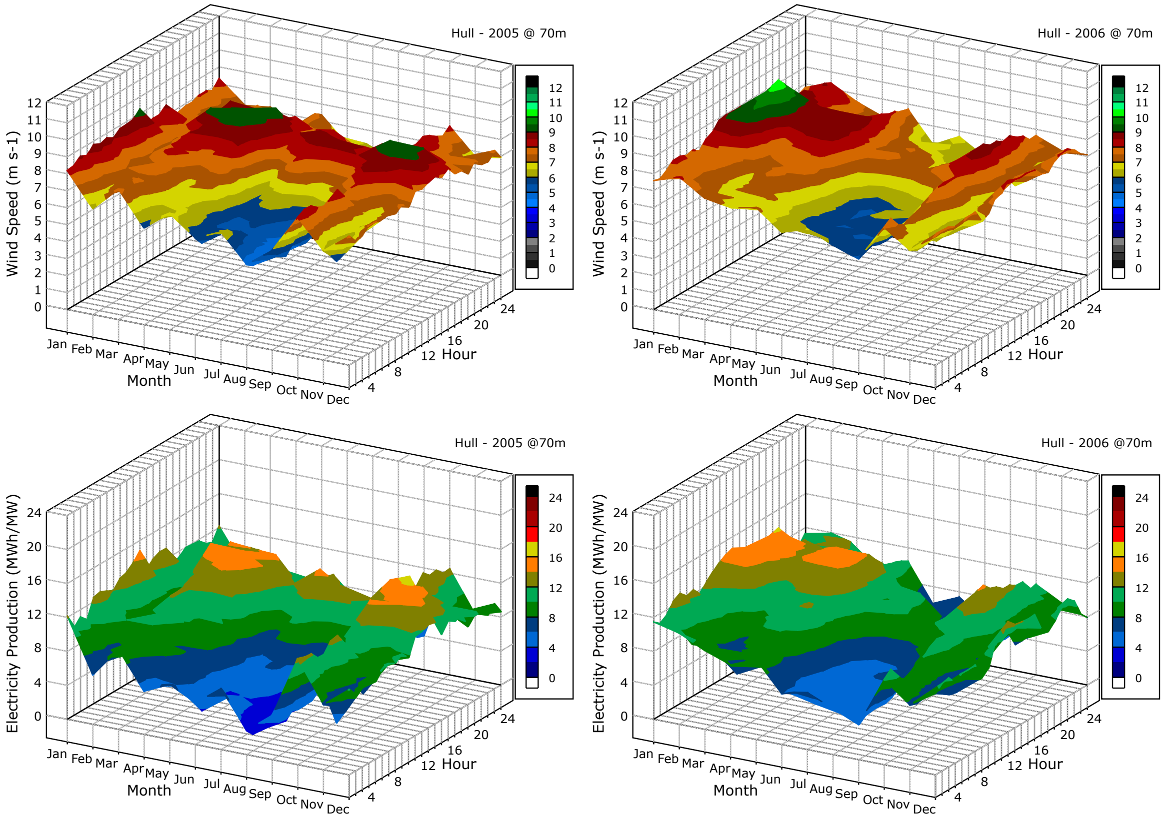
[2] Tony Rogers provided the wind-speed data based on the UMass researchers' measurements.

[3] My transformation of observed wind speeds to generation output follows the methodologies discussed in Berlinski [3]. His thesis documents in more detail each step above.

Figure 5-1: Hull Near-Shore Turbine - Wind Speed and Generation, 2005-2006



Electric 3.6 MW turbine. As above, these transformations followed the methodology in [3], which is fully documented in that report. Average wind speeds and generation output are shown by hour and month in Figure 5-2. The important characteristic of this dataset, as distinct from the near-shore set above, is the consistent seasonal pattern of high wind speeds during the winter months and lower wind speeds during summer months.

## Northborough Solar

*In situ* solar generation from an installation in Northborough, MA is used as an example solar dataset. The installation has a nominal capacity of 6.9 KW, generated by three 2.2 KW and one 300 W units. The output of the entire array is monitored for the National Grid Company by a contractor, New Energy Options, who provided the data[4]. Hourly data is available for most of 2003 and 2006 but no data is available for 2004 and only 4 months of 2005 are available. Generation output are shown for 2003 and 2006 by hour and month in

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[4] James Bing of New Energy Options graciously provided the data.

Figure 5-2: Nantucket Offshore Turbine - Wind Speed and Generation, 2005-2006

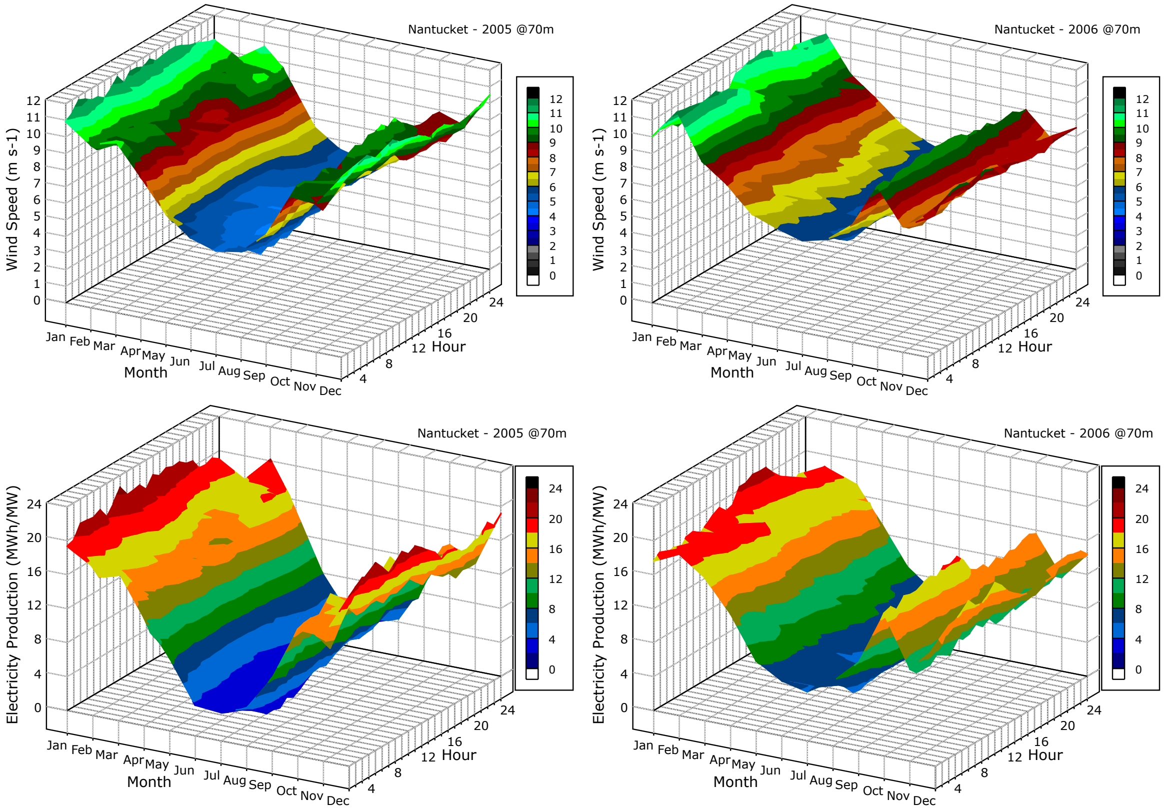

Figure 5-3.

## Simulated Solar

In order to supplement my analysis of the sparse *in situ* solar data set, I ran a similar analysis using simulated solar output based on typical weather conditions. The TRNSYS program[5] is used widely to simulate solar output based on National Renewable Energy Laboratory Typical Meteorological Year (TMY) data. I ran the simulation using TMY data for Worcester, MA (other locations were also analyzed with similar qualitative results) and a simple grid-tied crystalline photovoltaic panel with inverter. Default values suggested by TRNSYS were used for panel and inverter efficiency. The results of the simulation (which produces one year of output) are summarized in Figure 5-4.

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[5] Demo version available for download at http://sel.me.wisc.edu/trnsys/

Figure 5-3: Northborough Solar Installation Generation, 2003 and 2006

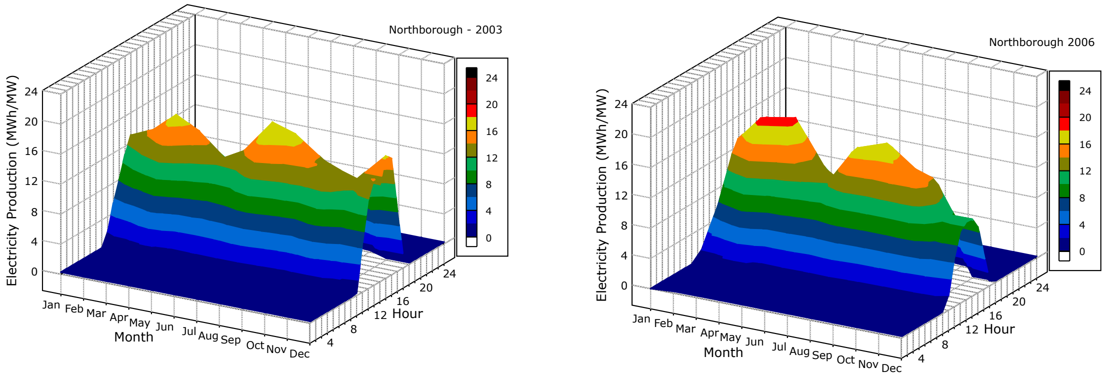
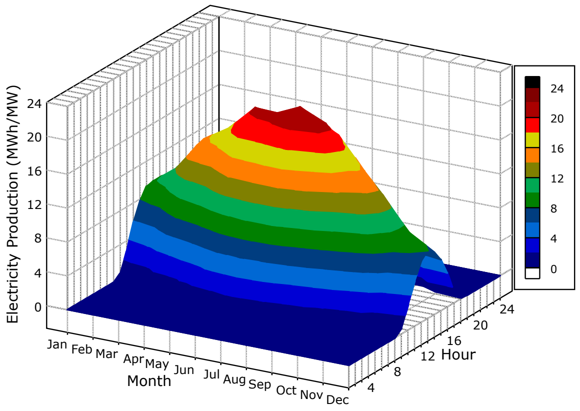


Figure 5-4: Simulated Solar Generation Based on Worcester, MA TMY



## 5.4 Intermittent Generator Results

Calculated revenues by year for each of the example sites are summarized in Table 5.1. This table reports revenue per MW installed for the flat-tariff scenario and the change in revenue under each RTP scenario, for each year. Revenues are also shown graphically in Figure 5-5. Both wind and solar lose revenue as a result of RTP, but both lose less per unit of capacity than the generation sector as a whole. As a percentage of the flat rate revenue, solar loses slightly less revenue than wind at each elasticity level. The higher utilization of wind capacity, though, means that in absolute terms, wind loses much more revenue per installed capacity than solar.

This analysis answers the first central question of this thesis: How would the revenue impacts of RTP on renewable generators compare to those on the generation sector as a whole.

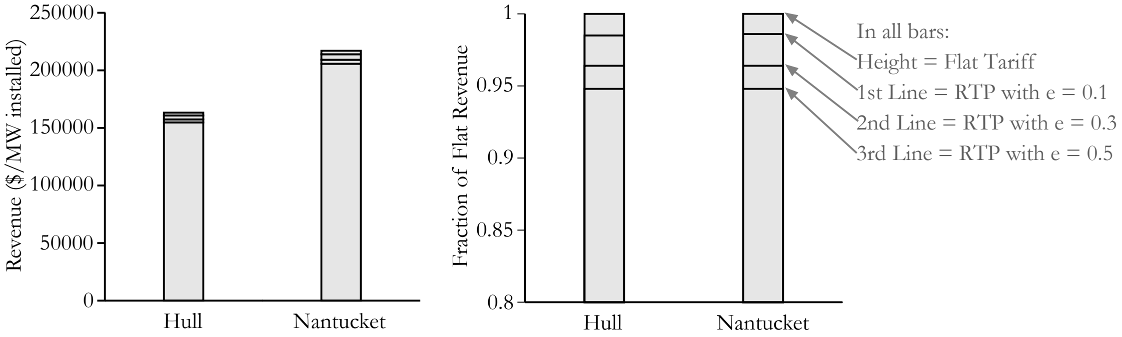
Table 5.1: Summary of Revenue Impacts on Intermittent Generators

| | | %Δ Revenue, RTP Compared to Flat | | |
|---|---|---|---|---|
| Year | Flat Revenue ($) | $\epsilon = -0.1$ | $\epsilon = -0.3$ | $\epsilon = -0.5$ |
| All Generation Sector | | | | |
| 2003 | 5.57B | -1.7 | -4.5 | -6.6 |
| 2004 | 6.71B | -3.0 | -7.2 | -10.2 |
| 2005 | 9.34B | -3.3 | -8.5 | -12.6 |
| 2006 | 7.40B | -1.5 | -4.0 | -6.0 |
| All Years | 29.02B | -2.5 | -6.3 | -9.2 |
| Hull Near-Shore Wind (Rev per MW installed) | | | | |
| 2003 | 127K | -1.1 | -2.9 | -4.4 |
| 2004 | 160K | -2.4 | -5.4 | -7.4 |
| 2005 | 205K | -1.5 | -4.0 | -6.0 |
| 2006 | 162K | -0.7 | -1.8 | -2.7 |
| All Years | 653K | -1.5 | -3.6 | -5.2 |
| Nantucket Off-Shore Wind | | | | (per MWi) |
| 2003 | 185K | -1.2 | -3.1 | -4.7 |
| 2004 | 205K | -2.4 | -5.4 | -7.5 |
| 2005 | 266K | -1.5 | -4.0 | -6.0 |
| 2006 | 211K | -0.6 | -1.6 | -2.5 |
| All Years | 868K | -1.4 | -3.6 | -5.2 |
| Northborough *in situ* Solar, incomplete data set (per MWi) | | | | |
| 2003 | 53K | -1.0 | -2.6 | -3.9 |
| 2004 - No Available Data | | | | |
| 2005 - No Available Data | | | | |
| 2006 | 70K | -1.1 | -2.6 | -3.8 |
| All Years | 123K | -1.0 | -2.6 | -3.8 |
| Worcester TMY Solar (per MWi) | | | | |
| 2003 | 63K | -0.6 | -1.7 | -2.6 |
| 2004 | 72K | -1.1 | -2.9 | -4.2 |
| 2005 | 104K | -1.5 | -3.8 | -5.7 |
| 2006 | 85K | -1.2 | -2.8 | -4.1 |
| All Years | 324K | -1.2 | -2.9 | -4.4 |

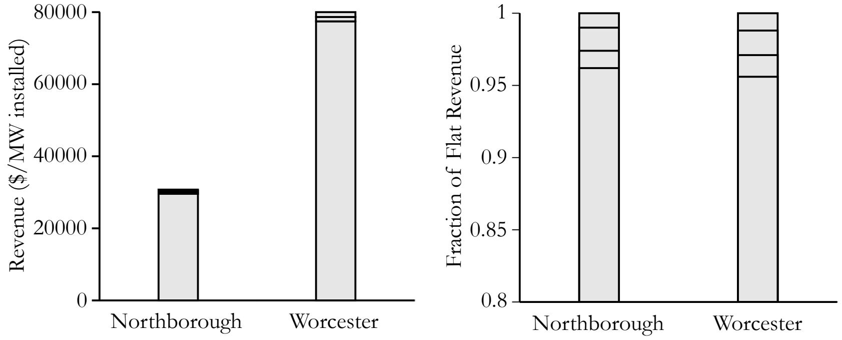
In Chapter 2 I proposed the hypothesis that solar generators would be particularly harmed by RTP, while wind generators may be better off. This analysis fails to provide support for

Figure 5-5: Change in Annual Revenue for Renewable Generators Due to RTP

**Wind Sites**



**Solar Sites**



either aspect of this hypothesis. According to this simulation, both wind and solar generators would lose revenue under RTP, but their losses would not be as great as the expected losses of the average generator. Ideally more generation sites would be considered before extrapolating this result, but it appears that RTP slightly increases the attractiveness (on a revenue basis, but not necessarily a profit basis) of both solar and wind generation compared to fossil, while at the same time decreasing the attractiveness of generation investment in general.

## 5.5 Load Factor Methodology

ISO-NE bid data does not reveal the fuel type of each bidding unit, so we cannot identify with certainty how RTP will effect the revenues of assets grouped by fuel type. Instead, we can use hourly regional load factor. Load factor refers to a fraction of generation capacity which is being used at any particular point. In my analysis I calculate load factor as the ratio of total load to the ISO-NE's reported available capacity, which is reported in ISO-NE's Daily Capacity Status document[20][6]. The load factor in hour $t$ and scenario $i$ is therefore calculated as

$$LF_{t,i} = \frac{Q_{t,i}}{AvailCap_t} \tag{5.2}$$

Regional load factor can serve as a proxy for which units are dispatched in a particular hour, and we can compare revenues in all hours with a load factor greater than some threshold to estimate the effects of RTP on certain classes of generators. If we ignore cost non-convexities and T&D constraints (as above), generation units will be dispatched in a similar order in each hour, determined by their relative marginal costs. In other words, if a certain unit has a marginal cost which is in the 80th percentile of all units in the region (weighted by capacity), that unit will be dispatched only in those hours where regional load factor exceeds 0.8. By comparing revenue changes in hours with load factors greater than 0.0 with those greater than 0.6, 0.8, or .95, we can develop a rough estimate of how RTP will differentially effect baseload, mid-merit, and peak generators, and critical peak generators.

## 5.6 Load Factor Results

Regional available capacity was only available to November 2005, so results are shown for two complete years from December 2003 to November 2005. The results, which are summarized in Table 5.2 and Figure 5-6, are as expected – those generators which are only dispatched in high-load factor hours will face significant revenue decreases as a)those hours become less frequent and b)the price in those hours falls.

Table 5.2 displays the clearest evidence of this result. For the RTP scenario with $\epsilon = -0.3$, a coal plant which may have marginal costs in the 30th percentile of all generators will see a loss of 7% of its hourly operating revenue, but an oil plant with marginal costs in the 80th percentile will see losses of 55%.

---

[6] Data were missing for a handful of days in this dataset. In those cases, I used the available capacity for the previous day in this calculation. There are no instances of consecutive days of missing data in the set.

Figure 5-6: Change in Annual Revenue by Generator Class Due to RTP

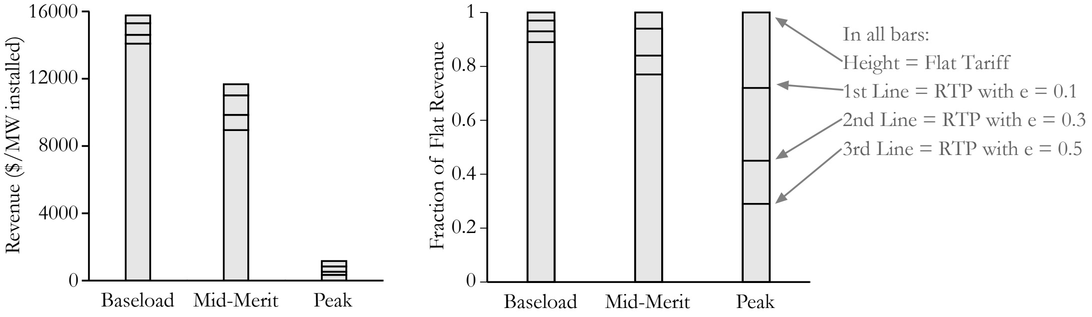


Figure 5-7 shows the cumulative distribution of hours by load factor under each scenario and Figure 5-8 shows the average operating revenue for hours at or above each load factor. These figures emphasize that higher marginal cost units will be dispatched less frequently *and* will see lower average revenues in the hours they are dispatched. Figure 5-9 shows the change in hourly operating revenue as a fraction of the flat-tariff average, again displaying large relative losses for high-marginal cost assets.

Figure 5-7: Cumulative Hours Above Load Factors, Dec. 2003 - Nov. 2005

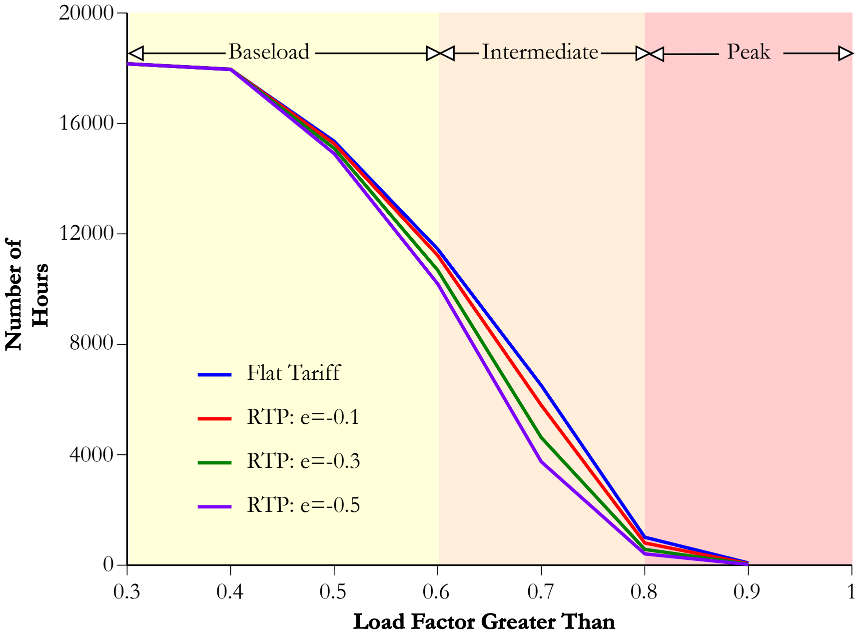
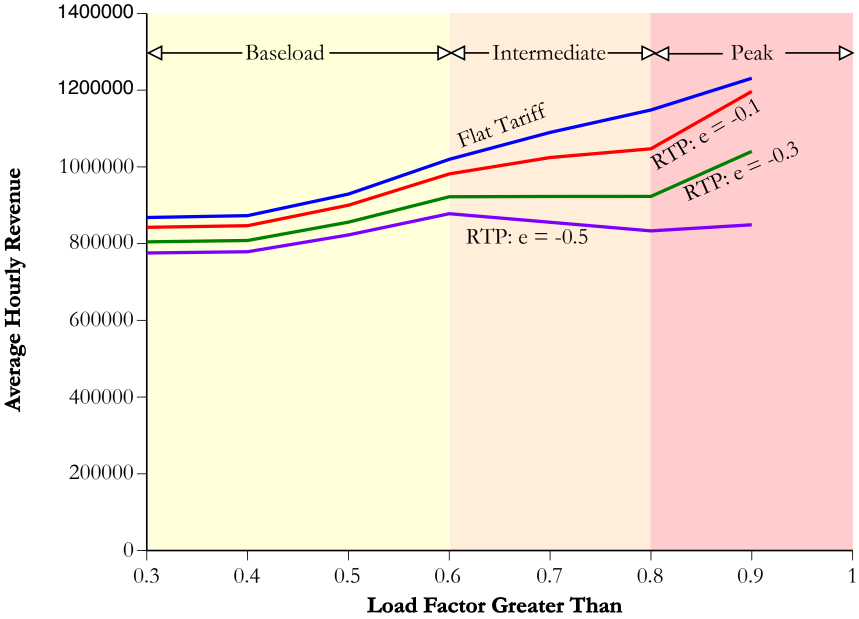


Figure 5-8: Average Hourly Revenue by Load Factor, Dec. 2003 - Nov. 2005



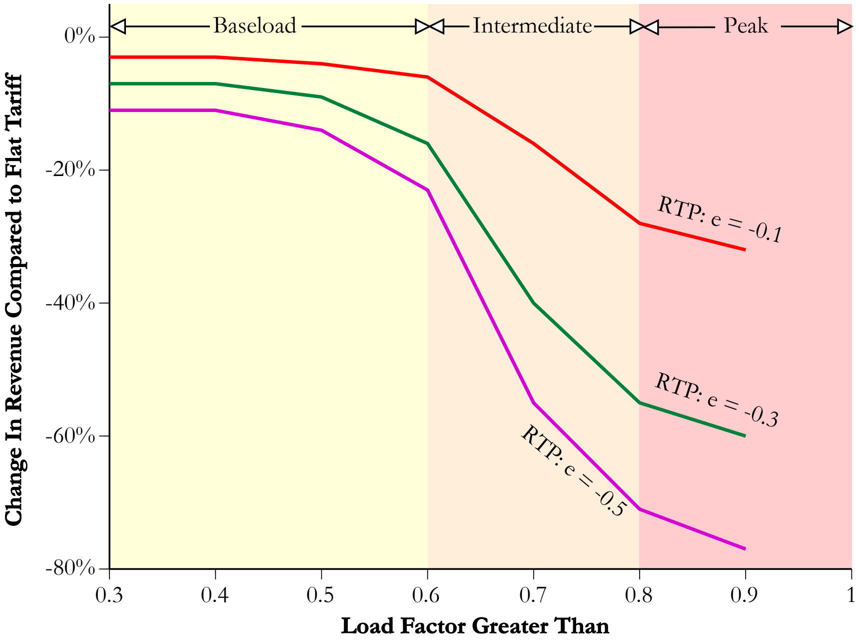
## 5.7 Discussion

Through the retrospective modeling of intermittent generator revenues from 2003-2006, I have shown that both the wind and solar generators considered should expect modest losses in revenue due to real-time pricing. This effect arises due to the lower average wholesale prices that price elasticity encourages, rather than a change in the quantity which renewable generators are able to sell.

Compared to many other generators, the expected revenue losses for renewable generators appear modest - a comparison which is summarized graphically in Figure 5-10. My analysis of revenue changes by load factor puts renewable losses in context. While the generation sector as a whole may lose 3-11% of revenue (based on elasticities of -0.1 to -0.5), generators with higher marginal costs may lose much more revenue - at least 70% for high-cost generators in high-elasticity scenarios.

In terms of profit, though, this apparent relative advantage may not exist. Renewable generators such as wind and solar have almost entirely fixed costs, meaning that any deviations in revenue translate almost entirely into deviations in profit. This is also the case with hydro and to a lesser extent nuclear generators, but different from fossil generators.

Figure 5-9: Change in Total Revenue with RTP Compared to Flat Tariff, by Load Factor, Dec. 2003 - Nov. 2005



Coal, gas, and oil generators have significant variable input costs, such that a loss of sales (and thus revenue) has an attenuated effect on profit. For example, if the break-even price of electricity required by a fossil plant represents 50% variable costs and 50% fixed costs, a loss of one unit of revenue translates to a half-unit loss of profit (since the other half was simply pass-through on variable costs). This implies that the results reported in this chapter should not be taken as conclusively good news for renewable generators, and may in fact indicate that RTP will counteract other policies designed to promote renewable generation (e.g. Renewable Production Tax Credits, Renewable Portfolio Standards, or Feed-In Tariffs).

The first objective of this research is to examine how RTP may change renewable generator revenues. The analysis of intermittent generators presented in this chapter shows that, while wind and solar are expected to lose revenues, their losses are somewhat less than the generation sector as a whole and much less than some high marginal-cost generators[7].

---

[7] Uncertainty remains as to how applicable these results may be in other regions. In New England, peak demand and peak solar output are not perfectly coincident, while in other regions (especially other temperature ranges) peak demand and solar output may be highly coincident. In that case, we may expect solar losses to be greater than those modeled here. Other resource availability regimes may also alter these results – wind sites with availability patterns which are distinctly different from those studied here may expect different effects. In general, this chapter has outlined a method of analysis with publicly available

This improved understanding will now be helpful in the discussion of Chapter Seven, which examines the political economy of real-time pricing with particular focus on producer interests. Before that, the next chapter will present the results of an additional analysis of the environmental effects of RTP.

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data, and future work could be dedicated to applying this method to a wider range of demand or resource availability regimes.

Table 5.2: Total Revenues by Cumulative Load Factor, 2004-2005 in New England

Panel A: Flat Tariff Results

| Load Factor | # of Hours | Avg. Hourly Revenue ($K) | Total Revenue ($M) |
|---|---|---|---|
| 0 - 1.0 | 18159 | $868 | $15763 |
| 0.5 - 1.0 | 15354 | $929 | $14266 |
| 0.6 - 1.0 | 11447 | $1020 | $11672 |
| 0.7 - 1.0 | 6511 | $1090 | $7096 |
| 0.8 - 1.0 | 1012 | $1148 | $1162 |
| 0.9 - 1.0 | 82 | $1231 | $101 |
| 1 - 1.0 | 3 | $2315 | $7 |

Panel B: RTP with $\epsilon$ = -0.1

| Load Factor | # of Hours | Avg. Hourly Revenue ($K) | %Δ Compared to Flat Tariff |
|---|---|---|---|
| 0 - 1.0 | 18159 | $842 | -2.9% |
| 0.5 - 1.0 | 15266 | $900 | -3.7% |
| 0.6 - 1.0 | 11218 | $982 | -5.7% |
| 0.7 - 1.0 | 5794 | $1024 | -16.4% |
| 0.8 - 1.0 | 804 | $1047 | -27.6% |
| 0.9 - 1.0 | 57 | $1197 | -32.4% |
| 1 - 1.0 | 0 | - | - |

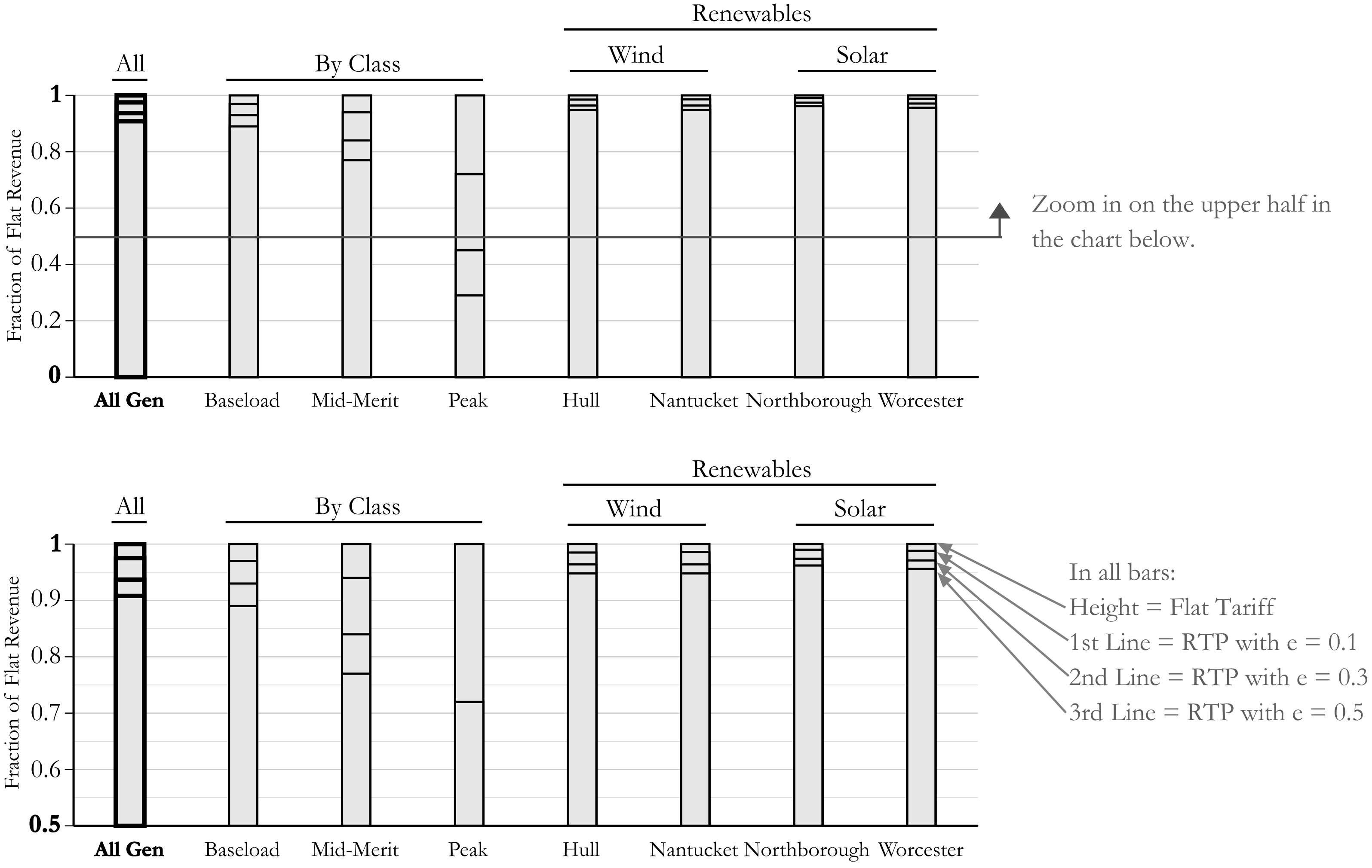
Panel C: RTP with $\epsilon$ = -0.3

| Load Factor | # of Hours | Avg. Hourly Revenue ($K) | %Δ Compared to Flat Tariff |
|---|---|---|---|
| 0 - 1.0 | 18159 | $805 | -7.3% |
| 0.5 - 1.0 | 15097 | $856 | -9.4% |
| 0.6 - 1.0 | 10683 | $922 | -15.6% |
| 0.7 - 1.0 | 4623 | $923 | -39.9% |
| 0.8 - 1.0 | 571 | $923 | -54.6% |
| 0.9 - 1.0 | 39 | $1040 | -59.8% |
| 1 - 1.0 | 0 | - | - |

Panel D: RTP with $\epsilon$ = -0.5

| Load Factor | # of Hours | Avg. Hourly Revenue ($K) | %Δ Compared to Flat Tariff |
|---|---|---|---|
| 0 - 1.0 | 18159 | $776 | -10.7% |
| 0.5 - 1.0 | 14907 | $823 | -14.0% |
| 0.6 - 1.0 | 10190 | $878 | -23.4% |
| 0.7 - 1.0 | 3746 | $856 | -54.8% |
| 0.8 - 1.0 | 410 | $833 | -70.6% |
| 0.9 - 1.0 | 27 | $849 | -77.3% |
| 1 - 1.0 | 0 | - | - |

Figure 5-10: Summary: Changes in Annual Revenue Due to RTP



Zoom in on the upper half in the chart below.

In all bars:
Height = Flat Tariff
1st Line = RTP with e = 0.1
2nd Line = RTP with e = 0.3
3rd Line = RTP with e = 0.5

# Chapter 6

# Short-Run Emissions Under Real-Time Pricing

## 6.1 Introduction

In addition to the welfare effects analyzed in the previous two sections, we can also use the model of RTP response in conjunction with marginal emissions rates developed in concurrent work at MIT in order to estimate the environmental impacts of RTP in New England. In this chapter I outline an analysis of short-run environmental impacts of RTP. I find that introduction of RTP should induce small decreases in emissions of $CO_2$, $SO_2$, and $NO_x$. For a moderate elasticity of -0.3, emissions of each pollutant should decrease by 2-3%, in line with the 2.3% expected decrease in quantity.

## 6.2 Methodology

The EPA's Continuous Emissions Monitoring (CEM) program reports hourly $CO_2$, $SO_2$, and $NO_x$ emissions from each fossil generating unit in the United States, as well as each unit's hourly power output. Research at MITs Laboratory for Energy and Environment (LFEE) has developed a method for identifying regional hourly marginal emissions rates of each pollutant using CEM data. The methodology is described in detail in LFEE reports [14] and is only outlined here.

The marginal emissions rate algorithm is outlined in Figure 6-1[1]. The rate of change of hourly total system load is calculated from load data available from ISO-NE [18], and each unit's power output and change in power output are calculated from CEM data. For each hour, the algorithm is as follows:

1. Calculate each unit's capacity as the maximum power output observed over the last six months.

2. Calculate each unit's capacity factor as the ratio of current output to unit capacity. Use this ratio to assign units to one of four load states according to the classifications in Table 6.1.

Table 6.1: Load State Classifications

| Unit Capacity Factor | Load State |
|---|---:|
| 0.00 - 0.05 | Turning On/Off |
| 0.05 - 0.55 | Standby |
| 0.55 - 0.90 | Spinning Reserve |
| 0.90 - 1.00 | Full Load |

3. Calculate each unit's change in power output $\Delta P = P_t - P_{t-1}$.

4. Calculate the change in total system load $\Delta Load = Load_t - Load_{t-1}$.

5. Flag each unit as Load-Shape Following if its load state is Spinning Reserve or its change in power output has the same sign as the change in total system load, i.e. $\Delta P * \Delta Load > 0$.

6. Calculate the hour's marginal emissions rate as the average of CEM-reported emission rates for all units flagged as Load-Shape following, weighted by the unit's change in power output, i.e.

$$MER_t = \frac{\sum_i LSF_{i,t} * ER_{i,t} * \Delta P_{i,t}}{\sum_i LSF_{i,t} * \Delta P_{i,t}} \tag{6.1}$$

where

---

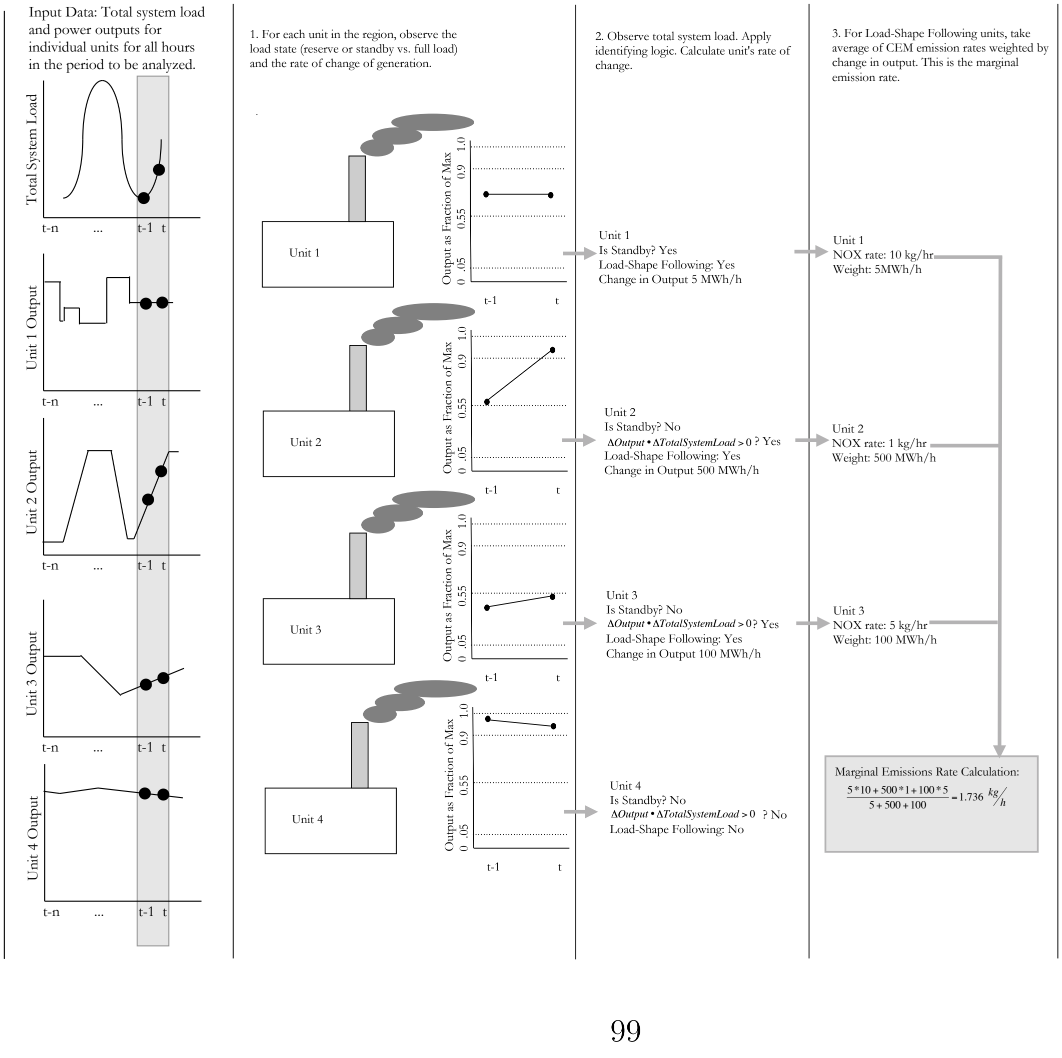
[1] The method is fully documented in the LFEE report [14]. The numbers used in this analysis were the output of an update to that report. The update will be documented in a forthcoming LFEE report by Tarek Rached, Stephen Connors, and I.

$MER$ = Regional Marginal Emission Rate
$ER_{i,t}$ = Emission Rate at Plant $i$ for Hour $t$
$P_{i,t}$ = Power Output of Plant $i$ for Hour $t$
$LSF_{i,t}$ = Load Shape Following Flag,
1 if identified above as LSF, 0 otherwise

## 6.3 Marginal Emissions Rates

Table 6.2 summarizes the calculated New England marginal emission rates over the study period. Marginal rates exhibit extremely high variance over time — the range of minimum to maximum spans three or more orders of magnitude for each pollutant. The distribution of emission rates over time is also skewed, shown in Figure 6-2. This figure also compares the median load-shape following rate with the median rate for the total system, showing that

Figure 6-1: Calculation of Marginal Emission Rates



emissions calculations based on system (non-LSF) rates are expected to be biased downwards.

Table 6.2: Marginal Emission Rates, Summary Statistics

| | 2003 | 2004 | 2005 | 2006 | All Years |
|---|---|---|---|---|---|
| $CO_2$ (kg/MWh) | | | | | |
| Min | 213 | 286 | 287 | 89 | 89 |
| **Mean** | **1140** | **1093** | **1558** | **1428** | **1304** |
| Max | 223387 | 303488 | 473232 | 1040000 | 1040000 |
| Min:Mean | 0.2 | 0.3 | 0.2 | 0.1 | 0.1 |
| Max:Mean | 196.0 | 277.7 | 303.7 | 728.3 | 797.5 |
| $SO_2$ (kg/MWh) | | | | | |
| Min | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Mean** | **1.6** | **1.9** | **1.5** | **2.3** | **1.8** |
| Max | 278.8 | 1261.1 | 628.5 | 1640.5 | 1640.5 |
| Min:Mean | 0.01 | 0.01 | 0.01 | 0.00 | 0.00 |
| Max:Mean | 170.0 | 678.0 | 424.6 | 710.2 | 901.4 |
| $NO_x$ (kg/MWh) | | | | | |
| Min | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| **Mean** | **1.1** | **0.7** | **0.8** | **0.7** | **0.8** |
| Max | 141.2 | 171.5 | 835.2 | 24.4 | 835.2 |
| Min:Mean | 0.03 | 0.05 | 0.04 | 0.01 | 0.01 |
| Max:Mean | 134.5 | 263.8 | 1006.3 | 35.3 | 1044.1 |

## 6.4 Results

Calculation of the first-order expected change in emissions due to RTP adoption is therefore a straightforward multiplication of the expected change in total load by the marginal emission rates for each hour. Figure 6-3 shows this process in time series for three days in July 2006. The top series shows observed load (in black) and load under RTP (in blue). This is followed by the change in load (i.e. the difference between flat and RTP load). The next six series show the hourly marginal emission rates followed by the expected change in absolute emissions for each of $CO_2$, $SO_2$, and $NO_x$.

Figure 6-2: LSF and System Emission Rate Distributions

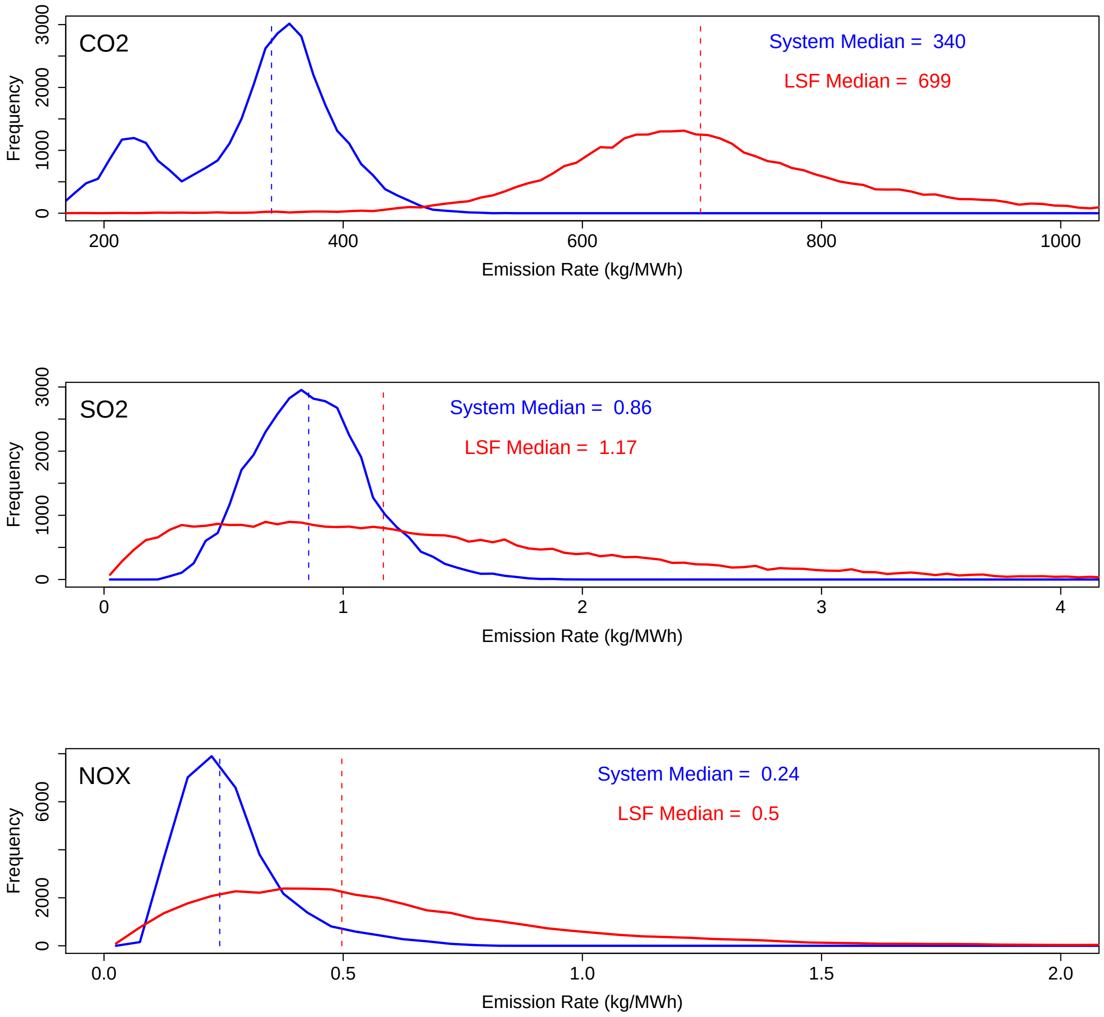


Figure 6-3: Time Series Change in Emissions Due to RTP

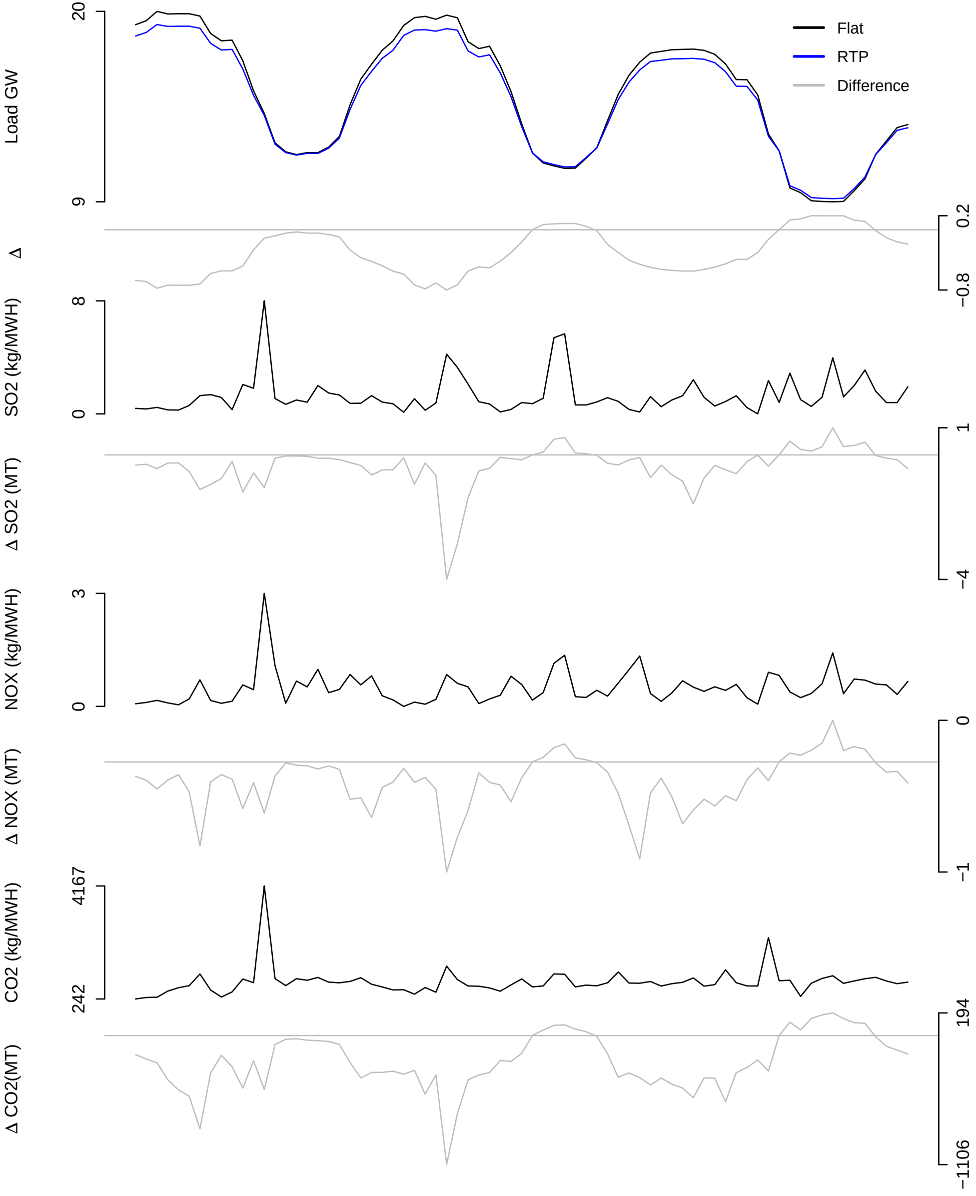


Table 6.3 summarizes the expected emissions changes summed over the entire study period. Figure 6-4 summarizes these results graphically.

Table 6.3: Counterfactual Emission Changes from RTP, as a Percentage Change from Flat Emissions

| Panel A: $CO_2$ | 2003 | 2004 | 2005 | 2006 | Four-Year Total |
|---|---|---|---|---|---|
| Flat ($10^9$ kg) | 86 | 87 | 81 | 101 | 355 |
| $\epsilon$ = -0.1 | -0.5 | -1.0 | -1.5 | -0.5 | -0.9 |
| $\epsilon$ = -0.3 | -1.4 | -2.7 | -4.2 | -1.4 | -2.4 |
| $\epsilon$ = -0.5 | -2.1 | -4.1 | -6.3 | -2.2 | -3.6 |
| Panel B: $SO_2$ | 2003 | 2004 | 2005 | 2006 | Four-Year Total |
| Flat ($10^6$ kg) | 236 | 229 | 209 | 285 | 958 |
| $\epsilon$ = -0.1 | -0.5 | -0.7 | -1.0 | -0.3 | -0.6 |
| $\epsilon$ = -0.3 | -1.3 | -1.8 | -2.8 | -1.0 | -1.6 |
| $\epsilon$ = -0.5 | -1.9 | -2.8 | -4.3 | -1.5 | -2.5 |
| Panel C: $NO_x$ | 2003 | 2004 | 2005 | 2006 | Four-Year Total |
| Flat ($10^6$ kg) | 78 | 68 | 63 | 77 | 286 |
| $\epsilon$ = -0.1 | -0.8 | -1.1 | -1.9 | -0.6 | -1.1 |
| $\epsilon$ = -0.3 | -2.2 | -2.9 | -5.2 | -1.6 | -2.9 |
| $\epsilon$ = -0.5 | -3.3 | -4.4 | -7.9 | -2.4 | -4.3 |

This analysis is predicated on the assumption[2] that the change in load, in this case due to RTP, has the effect of scaling up or down the output of LSF units. While in most hours the change in load is within the total LSF capacity, it is likely that introduction of RTP may shut down some units in the short-run or shift the equilibrium mix of generators in the long-run, creating second-order effects. To the extent that shut-down on the margin occurs, the marginal (LSF) emission rates are expected to shift towards the average (total system) rates. Examining Figure 6-2 reveals that, for all three pollutants considered, we expect RTP to shift the marginal (LSF) emissions rate downward[3].

A shift in marginal emission rates in turn imposes private costs or benefits on market par-

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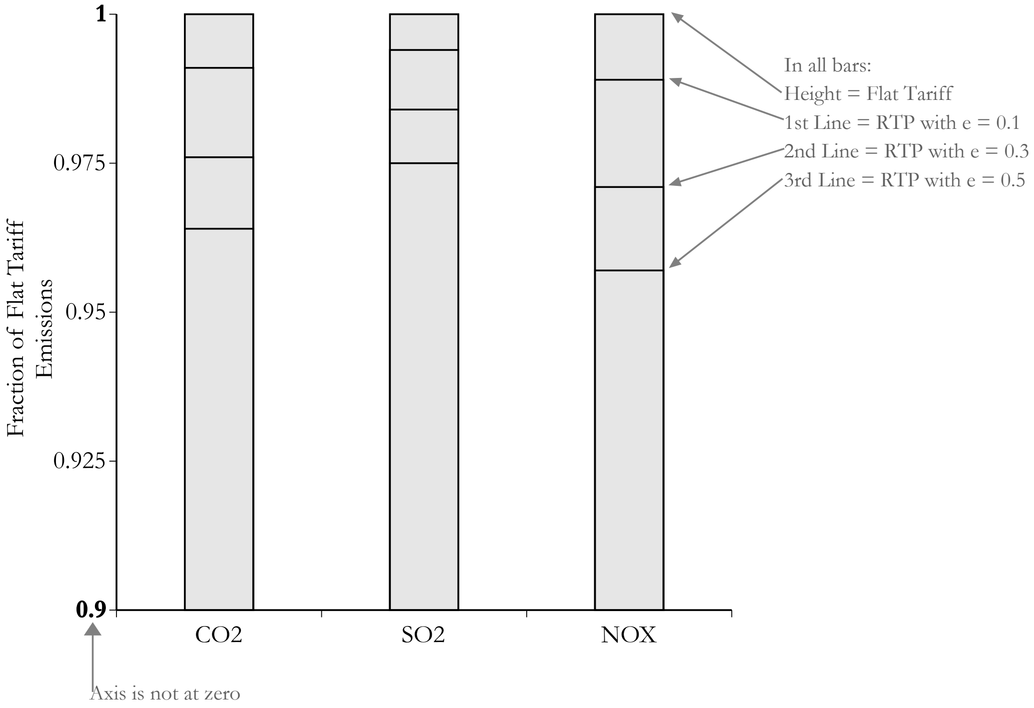
[2] Made in other LFEE reports, including [14] and our current advisory projects for proposed renewable developments.

[3] This speculation ignores the effect of emission regulations. Emissions of $SO_2$ and $NO_x$ may be limited by current emissions regulations which a) cap emissions across the region or b) limit emissions from new plants due to new source review. No current regulation has a similar limiting effect on $CO_2$ emissions, but the Regional Greenhouse Gas Initiative or similar policies at the federal level may change this in the coming years.

Figure 6-4: Summary Change in Emissions Due to RTP



ticipants who rely on marginal rates for some aspect of their permitting or revenue streams. Lower marginal rates, for example, will decrease the expected avoided emissions from proposed renewable generation or end-use efficiency investments and may therefore decrease their likelihood of being permitted or funded. Once constructed, renewable generators may rely on the sale of emissions offset credits for a significant fraction of their revenue stream. When these offsets are calculated on the basis of marginal emission rates, a shift in marginal rates will translate into a change in revenues from offset credit sales. In both these cases, the adoption of RTP imposes private costs on some profit-seeking participants. In other regions where marginal rates are lower than average rates[4], RTP adoption endows those same participants with private benefits. While I will not attempt to quantify this result, it may be important to consider such second-order effects in future analyses.

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[4] This might be the case, for example, in the Southeast, where most baseload generation is provided by coal.

## 6.5 Discussion

Using marginal emission rates developed from EPA Continuous Emissions Monitoring data together with my RTP market simulation, I have modeled the first-order impact that RTP introduction would have on regional emissions of $CO_2$, $SO_2$, and $NO_x$. In contrast to the small increase in short-run $SO_2$ and $NO_x$ emissions rates simulated by Holland and Mansur[21][5] for the PJM market, I find small decreases in all three short-run emissions due to RTP introduction in New England. Taken together with Holland and Mansur's [22] econometric estimation of the relationship between load variation and emissions, which failed to find a significant relationship between the two for any pollutant in the New England power pool, the evidence suggests that RTP will have minimal short-run impacts on annual emission rates in New England. RTP will alter the timing of emissions, though, which may be particularly important in considering the effect of $NO_x$ on ozone formation and could be the focus of future work. In addition, the results of my analysis should not be extrapolated to other regions, where the mix of fuels used at the margin may be different. The impact of RTP on long-run emissions is not examined with this analysis, and future work could be directed at that research question.

Having used my market simulation to assess the economic impact on various producers (in the previous chapter) as well as the regional environmental impact of RTP, I now turn to a comprehensive discussion of how these impacts fit in with the system-wide sources of support and opposition for RTP. In the next chapter I discuss how various stakeholders are likely to support or oppose RTP, drawing on the analysis in the previous chapters, other studies of RTP, and political theory to better understand these interests and how they might be effectively managed.

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[5] Discussed in Chapter 3.

# Chapter 7

# Political Economy and Support for RTP

## 7.1 Introduction

Introducing demand elasticity to electricity markets, via real-time pricing (RTP), is expected to increase economic efficiency and decrease distortions due to market power, while having uncertain effects on environmental and security externalities associated with electricity generation. On purely economic terms, RTP increases total welfare and, if implemented along with some Hicksian compensation scheme to compensate those generators who face private losses due to RTP, should constitute a Pareto-improving policy. Why, then, is RTP not the dominant price schedule in the U.S. retail power market?

The work presented in this thesis and elsewhere [10, 21, 8, 41] suggests that costs and benefits of RTP are unevenly distributed, with benefits diffuse among all consumers and costs concentrated among a small number of generators. At the very least, this situation represents an archetypal collective action dilemma [35], although other theories of political economy suggest that there may be multiple barriers to RTP support. In the following chapter I discuss the interests of various stakeholders, including the renewable generators studied above, in the context of theories of political economy. To understand the political pressures associated with an RTP policy, we must examine how much different groups stand to loose or gain, and also whether they will notice, whether they will care, and their potential for organization and coordination in applying political pressure.

## 7.2 Consumers, Prospects, and Collective Action

As a whole, consumers stand to gain modest short-run and significant long-run reductions in their electricity bill. These benefits are dispersed among millions of consumers, and benefits will be captured by all consumers regardless of the resources they commit to supporting RTP policies. Additionally, the absolute benefit of RTP is small for most residential and many small commercial users (savings of perhaps \$40/month on a \$200/month bill, 15-20 years from now). Two theories - the collective action dilemma [35] and prospect theory [43]- together strongly suggest that RTP policies in the system described above are unlikely to receive support from consumers in general.

At the individual level, prospect theory suggests that the framing of gains and losses has a significant impact on one's likelihood to act to secure or prevent a gain or loss. Specifically, the evidence supporting prospect theory [43, 27] suggests that losses are more cognitively affective than gains, especially in low-deliberation decisions. Because consumers are likely to perceive the flat tariff and associated deadweight loss as the status quo, a shift to RTP is framed as a gain (rather than the prevention of a loss), which has a lower absolute utility value than the equivalent loss. In other words, prospect theory suggests that while the net benefit of RTP to consumers is *positive* in real dollars, it may have *negative* net utility because the somewhat smaller monetary losses for some consumers are weighed more than the somewhat larger monetary gains for others.

At the organizational level, Olson's collective action dilemma [35] suggests that even if consumers are enticed by the prospect of gains from RTP, they will face difficulties in mobilizing resources to support RTP. Consumers will benefit from RTP whether or not they commit resources to its support. Given that the benefits to inaction (free-riding) are the same as the benefits to action (committing resources to supporting RTP), this theory suggests that consumers in general will choose to free-ride and erode support for RTP.

While the consumer sector as a whole faces difficulties in coordinating support for RTP, Olson suggests that a smaller group could be successful if its members face more significant losses or gains and are able to influence one another through peer pressure or selective benefits. Borenstein's [8] results, discussed previously, show that particular industrial users have huge savings under RTP. This concentration of benefits can explain why the only (non-experimental) implementations of RTP in the US are offered to industrial consumers, as shown in Chapter 3. Data on exactly which customers are on RTP, their industries, etc. are not readily available, but we may still speculate on some traits of these large consumers. Unlike end-users as a whole, large industrial users are small in number, face utility bills that are a significant component of their consumption bundle, and may be easily organized by existing industrial trade and lobbying groups. Firms may also be connected in ways unrelated to electricity consumption, e.g. through common suppliers or customers, social networks, or joint ventures in transport/logistics or waste disposal. These factors suggest that Olson's dilemma will not hinder industrial support for RTP [35].

There may be some difference, though, in how incumbent and potential industrial consumers support RTP. In those industries where electricity is a major component of costs, RTP may create opportunities for new firms to enter with capital equipment which is better able to minimize cost in the face of dynamic electricity prices. For example, a new manufacturing firm who could design its plant and process to respond quickly to high prices by temporarily shifting to less electricity-intensive tasks or processes could gain a cost advantage over an incumbent whose plant and process was designed assuming flat electricity rates. Incumbents who sense this vulnerability may actually oppose RTP even if it lowers their own costs. Since this example is purely speculative, future research should be directed at identifying such situations and measuring their implications.

## 7.3 Producer Interests and Collective Action

In order to develop a feel for the distribution of interests in the producer sector, I examined the ISO-NE Seasonal Claimed Capability report from October 2007 [16]. This report lists the capacity of each generation unit in New England along with its fuel type and primary owner. If we aggregate capacity by fuel and by owner, we can develop a sense of the market's ownership concentration by fuel, and the diversification of fuels by owner. The aggregations by fuel type, summarized in Table 7.1, show that there is much more concentration among baseload generators than intermediate and peak generators. The five largest owners of nuclear, coal, and hydro generation control 100%, 96%, and 83% of the share of power generated by those fuels, respectively, while the five-firm concentration in gas and oil is around 60%. Table 7.2 shows the holdings of the largest owners of generation in each fuel class – for example DEM, the largest holder of coal generation, also owns a large amount of nuclear and smaller amounts of oil and gas. A diversity of holdings may make a firm more likely to resist RTP, which hurts oil and gas more than baseload generation. Table 7.2, however, shows that the largest holders of baseload generation are also concentrated in baseload generation. The concentration of interest by fuels (Table 7.1) and within firms (Table 7.2) suggests that baseload generators may have more ability to coordinate in order to influence policies. However, the New England analysis presented above suggests that only peak generators expect major revenue loss from RTP. It is therefore unclear whether the private benefits of RTP would motivate a strong response from the baseload generators to RTP policies.

Incumbent peak generators, though, face significant private costs under RTP. Even though the number of firms is greater, policymakers should expect significant resistance from this segment. Further, because peak and baseload generators are connected in other ways (e.g. through lobbying groups or minority ownership, which is not examined in this analysis), we may actually expect baseload generators to commit resources to opposing RTP in order to align the industry's overall position.

It is important to note that new entrants to generation (whether peak or base) are likely to be ambivalent regarding RTP. Because they would be able to evaluate their investment with RTP, assets which are not profitable under an RTP regime will not be developed. While load response will decrease the total capacity required to serve load, thereby reducing the investment opportunities in this industry, as long as investors have other profitable ventures available to them, they should be indifferent to RTP. The loss to peak generators discussed in this report, then, is limited to existing producers, and if RTP is implemented the importance of peak producer losses will decay as the generation stock turns over.

Finally I consider the case of intermittent or renewable generators, the focus of the

Table 7.1: New England Generation Market Concentration by Fuel

| | Coal | Gas | Hydro | Nuclear | Oil | Other | Wind | Total Assets |
|---|---|---|---|---|---|---|---|---|
| Total Capacity | 2788 | 12826 | 3478 | 4588 | 8685 | 1084 | 1 | 33450 |
| Number of Firms | 6 | 27 | 40 | 3 | 35 | 29 | 3 | 85 |
| Share of Top Firm | 52% | 21% | 36% | 44% | 21% | 18% | 86% | 15% |
| 5-firm Concentration | 96% | 55% | 83% | 0% | 62% | 55% | 0% | 45% |
| HHI | 3328 | 910 | 2003 | 3518 | 1065 | 868 | 7620 | 611 |

empirical work in Chapter Five. The interests of renewable investors who hold significant assets in peak or baseload generation are likely to be aligned with those of other peak or baseload generators, since the amount of generation and revenue is so much greater from those sources. Existing investors who own primarily renewable assets are expected to oppose RTP more than price-taking fossil generators, as it imposes higher profit losses on renewables. Since renewables such as wind and solar have close to zero marginal operating cost, revenue losses translate almost completely into profit losses, putting renewables at a greater disadvantage than their revenue numbers indicate.

## 7.4 Tariff Choice, Diminishing Returns, and Free-Riding

The issue of free-riding, discussed above in the context of collective action, is more complicated when RTP is an optional price schedule that consumers can choose. As more consumers select RTP, the load profile will smooth, lowering rates for all consumers (not just those on RTP) and reducing the incentive for RTP adoption by the remaining flat-rate consumers. This free-riding effect could limit the adoption of RTP. To see this, consider the causal loop diagram[1] shown in Figure 7-1. RTP initially offers some advantage to some consumers (particularly those whose demand profiles are non-peak coincident), so these consumers adopt RTP. By responding to prices, RTP customers reduce wholesale market volatility, reducing average prices for all consumers. If RTP adoption offers some fractional reduction in costs

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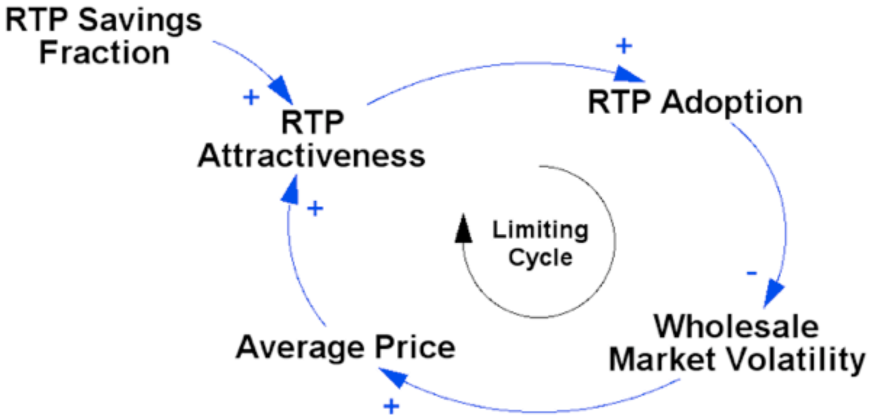
[1] The *causal loop diagram* is a conceptual map of causal influence. An arrow indicates a causal relationship, and the polarity of the arrow, indicated by the "+" or "-" sign, indicates the sign of the association. Put more specifically, a positive link from $A$ to $B$ indicates that an increase in $A$ will produce an increase in $B$, all else equal. A negative link indicates that an increase in $A$ will cause a decrease in $B$, all else equal.

Table 7.2: Holdings of New England Generation Companies by Fuel Type

| | Holdings by Fuel Type (MW capacity) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Holding Company | Coal | Gas | Hydro | Nuclear | Oil | Other | Wind | Total Assets |
| Largest Holders of Coal Assets | | | | | | | | |
| DEM | 1449 | 510 | 0 | 2037 | 889 | 41 | 0 | 4927 |
| PSNH | 532 | 0 | 97 | 0 | 503 | 116 | 0 | 1249 |
| PSEG | 370 | 0 | 0 | 0 | 617 | 0 | 0 | 987 |
| CLP | 182 | 39 | 25 | 0 | 0 | 110 | 0 | 356 |
| NEEM | 146 | 0 | 1267 | 0 | 21 | 0 | 0 | 1434 |
| NRGPM | 109 | 158 | 0 | 0 | 1807 | 0 | 0 | 2073 |
| Largest Holders of Gas Assets | | | | | | | | |
| SET | 0 | 2724 | 0 | 0 | 571 | 0 | 0 | 3295 |
| ANP | 0 | 1201 | 0 | 0 | 0 | 0 | 0 | 1201 |
| FPL | 0 | 1199 | 37 | 1245 | 869 | 0 | 0 | 3351 |
| DPM | 0 | 1062 | 0 | 0 | 0 | 0 | 0 | 1062 |
| LRGC | 0 | 820 | 0 | 0 | 0 | 0 | 0 | 820 |
| AESL | 0 | 798 | 0 | 0 | 0 | 0 | 0 | 798 |
| CEEI | 0 | 712 | 11 | 0 | 683 | 0 | 0 | 1406 |
| TPM | 0 | 635 | 539 | 0 | 0 | 0 | 0 | 1175 |
| BELP | 0 | 551 | 0 | 0 | 0 | 0 | 0 | 551 |
| CEN | 0 | 544 | 0 | 0 | 0 | 0 | 0 | 544 |
| DEM | 1449 | 510 | 0 | 2037 | 889 | 41 | 0 | 4927 |
| Largest Holders of Hydro Assets | | | | | | | | |
| NEEM | 146 | 0 | 1267 | 0 | 21 | 0 | 0 | 1434 |
| BSP | 0 | 0 | 595 | 0 | 0 | 0 | 0 | 595 |
| TPM | 0 | 635 | 539 | 0 | 0 | 0 | 0 | 1175 |
| FPLEMH | 0 | 0 | 348 | 0 | 0 | 0 | 0 | 348 |
| BEM | 0 | 0 | 149 | 0 | 0 | 0 | 0 | 149 |
| Largest Holders of Nuclear Assets | | | | | | | | |
| DEM | 1449 | 510 | 0 | 2037 | 889 | 41 | 0 | 4927 |
| ENPM | 0 | 0 | 0 | 1305 | 0 | 0 | 0 | 1305 |
| FPL | 0 | 1199 | 37 | 1245 | 869 | 0 | 0 | 3351 |
| Largest Holders of Oil Assets | | | | | | | | |
| NRGPM | 109 | 158 | 0 | 0 | 1807 | 0 | 0 | 2073 |
| MET | 0 | 249 | 0 | 0 | 1148 | 0 | 0 | 1397 |
| DEM | 1449 | 510 | 0 | 2037 | 889 | 41 | 0 | 4927 |
| FPL | 0 | 1199 | 37 | 1245 | 869 | 0 | 0 | 3351 |
| CEEI | 0 | 712 | 11 | 0 | 683 | 0 | 0 | 1406 |
| PSEG | 370 | 0 | 0 | 0 | 617 | 0 | 0 | 987 |
| MMWEC | 0 | 0 | 0 | 0 | 595 | 0 | 0 | 595 |

Figure 7-1: Feedback May Limit Total Adoption of RTP



relative to the flat-rate service, lower average prices will lower the absolute savings potential from RTP, which decreases the incentive for others to adopt.

Black [4] develops a dynamic simulation model to study a similar effect in the adoption of smart appliances, i.e. appliances with automated controls that can respond to electricity prices in real time. The adoption of these appliances is similar to RTP adoption – using a smart appliance reduces wholesale market volatility and therefore the incentive for others to adopt the smart appliance. The cost of the new appliance in this situation is analogous (but not equal in magnitude) to the cost of risk when considering RTP. The existence of a switching cost and the diminishing returns to adoption mean that both smart appliance and RTP adoption may be limited below socially optimal levels. Using behaviorally realistic parameters in his model, Black finds that smart appliances may be limited to 30-40% penetration in the classic PJM market.

## 7.5 Barriers to Even Pareto-Dominant Policies

The list of barriers to political support for policies, beyond the problems of framing, collective action, and diminishing returns cited above, is probably long and I will not attempt an exhaustive list. Two additional barriers that may be particularly relevant to the issue of RTP, though, are identified by Stiglitz [39] as common factors in the failure of many Pareto-improving policies.

First, Stiglitz cites the inability of government to make commitments. Interest groups may withhold support for a policy which is in their interest if they feel the government is insufficiently committed to protecting their interests. In the case of RTP, this may be a particularly strong barrier to producer support even when producers are offered Hicksian compensation in excess of their expected revenue losses. Generators will discount the value of government-promised compensation according to the risk that future politicians may redirect policy and cut compensation prematurely. Many electricity generators in liberalized U.S. markets have direct experience with this type of policy change. Before restructuring, state regulators guaranteed returns on investments made by investor-owned utilities, but in the restructuring process many of these guarantees were rescinded, leaving generators with suddenly unprofitable assets. In light of this experience, generators may be hesitant to enter into long-term compensation agreements with the government.

Stiglitz also identifies the costs of uncertainty in blocking support for pareto-improving policies. Stiglitz describes the political bargains that must take place to adopt policy as similar to traditional markets in their information asymmetries. In any market with information asymmetry, the seller has access to more information about the true value of a good than a buyer, so buyers may not be able to determine whether a trade is really in their interest and otherwise beneficial trades may not take place[2]. In the case of RTP, consumers are uncertain about how much they may actually save under RTP adoption (academic studies cited previously notwithstanding) and producers face even more uncertainty in determining how much RTP will cost in lost revenues. Estimation of these costs depends on forecasting technological development of price-responsive electricity loads over 25-40 years, an exceptionally uncertain exercise. Stiglitz hypothesizes that in the face of uncertainty, political opponents who are offered a pareto-improving opportunity may turn it down on the assumption that the offerer has private knowledge that the policy is not actually in the offerree's best interest. While "opponents" may be too harsh in describing the relationship between regulators and power producers, it is possible that producers will view any compensation offers from regulators with skepticism.

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[2] The classic lemons market [1].

## 7.6 Political Processes and Real-Time Pricing

The barriers to action on RTP policy are in part archetypal political issues and in part an outcome of the particular architecture of restructured electricity markets. In this closing section I highlight one approach which may help to overcome these barriers – Hicksian compensation.

*Hicksian compensation* refers to the compensation that would maintain an actor's utility at the same level after some change. In the case of RTP, Hicksian compensation would be directed at those producers who stand to loose money on investments that would have been profitable under the flat-tariff regime. Since the real benefit of RTP is in removing the incentive to over-invest in future peak capacity, compensation by consumers (who benefit from RTP) to only the *current* peak producers (who loose from RTP) may overcome their resistance while leaving in place the more efficient long-run investment incentives that RTP creates. This may take the form of a small, fixed tax on electricity sales which is redistributed to generators in proportion to their lost revenues and phased out over a fixed period. While this sounds complicated and may be objectionable to some consumer advocates, there is precedent for precisely this sort of bargain in electricity regulation. When states liberalized their markets in the 1990s, most introduced a system charge that repaid utilities for their stranded costs. State regulators already have access to many generators cost and debt structures, so using this information to modify the stranded cost recovery that is already in place may be a feasible way to manage such a bargain. In this case, dedicated state regulators may be able to introduce RTP even when support from those who benefit (i.e. the public at large) is tepid.

## 7.7 Stakeholder Positions and Capacity for Motivation

In this chapter I have examined why RTP is not a widely implemented policy, given that it is welfare improving. The stakeholder positions I examine above can be summarized as follows:

- Consumers whose demand is peak coincident are likely to oppose RTP. This group is likely to include many classes of consumers, including residential, commercial, and industrial. Their change in electricity costs due to RTP is currently framed as a loss, increasing their aversion to the policy.

- Consumers whose demand is not peak coincident, or those that can easily respond to prices, have economic incentives to support RTP. The magnitude of their support, however, is likely to be limited by 1) the framing of these benefits as a gain rather than a foregone loss and 2) the ability of free-riders to reap the same benefits as those who dedicate resources to supporting RTP.

- Incumbent producers are likely to strongly oppose RTP. Peak-producers, in particular, face dramatic private costs under RTP and are likely to dedicate significant resources to resisting the policy.

- Renewable generators, to the extent that their shareholders are not invested in fossil assets, may be ambivalent about or oppose RTP, depending on their expectations regarding RTP's effect on long-run competitive dynamics in generation (which I have not examined) versus the small short-run loss they face under RTP.

This discussion leads to recommendations to various actors in the policy debate. *First*, those that push RTP for efficiency/welfare reasons must understand that political support is unlikely without compensation to those incumbent generators who stand to lose under RTP. The compensation policy must be credible and developed in an open process so that all participants understand what one another stand to lose and gain. *Second*, those that develop electricity policy in general must understand that policies implemented to achieve an isolated benefit (such as economic efficiency) may impact the ability to meet other regulatory objectives (such as in air quality or industrial policy)[3]. In this case, these results highlight the need for policymakers to understand the higher-order effects of their policies in order to achieve their objectives most effectively.

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[3] A convincing argument is made for increasing the fungibility of these three objectives by internalizing external costs and benefits into private decisions, and it is possible that complete internalization would allow policy development to then be a simple exercise of maximizing a single objective. Electricity markets, though, are far from this situation, so that in reality we must consider policy tradeoffs over multiple objectives.

# Chapter 8

# Conclusion

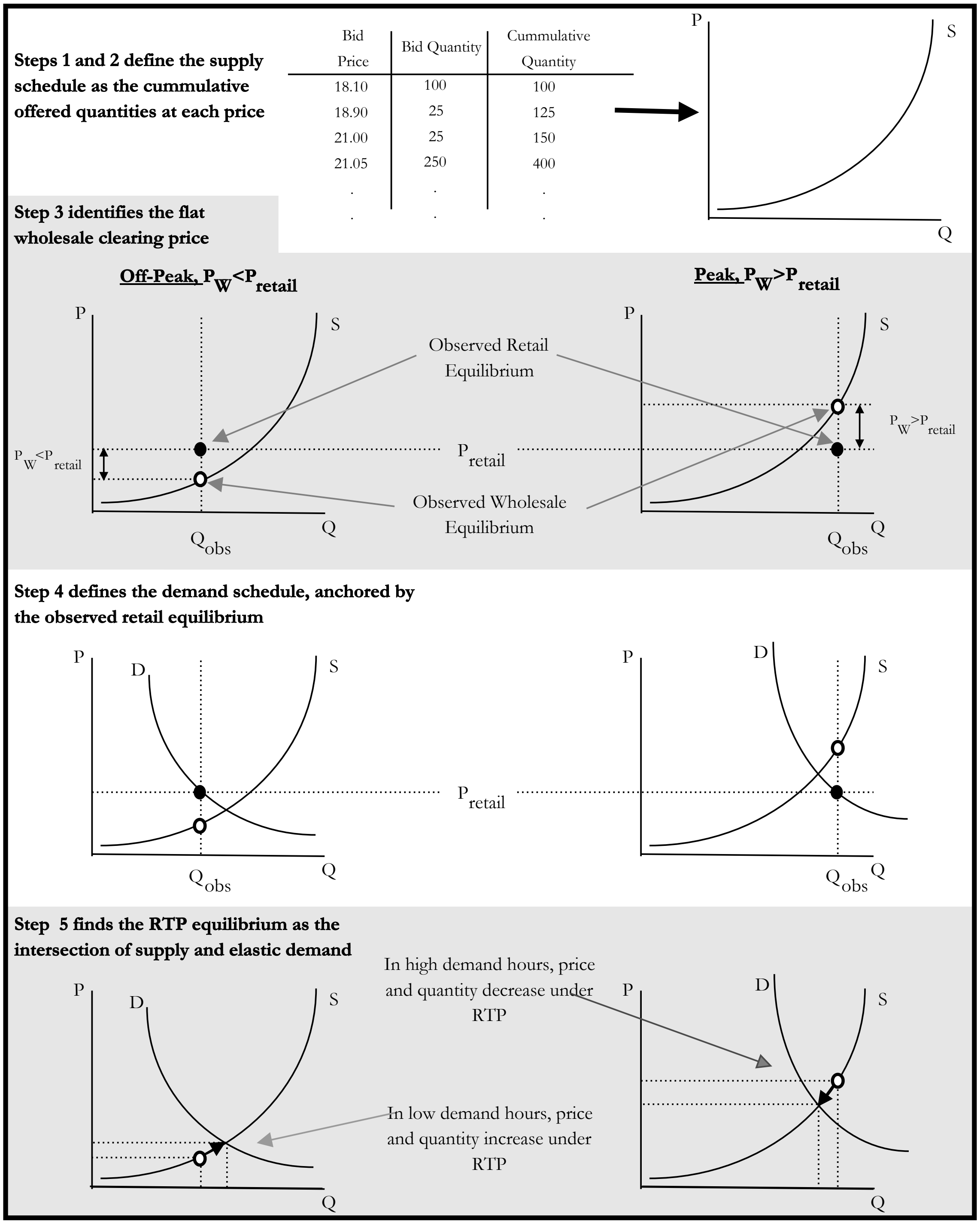
The objectives of this research were threefold. First, I explored the effect that real-time retail pricing of electricity would have on intermittent, renewable generators' revenues, a question which was not previously studied. Second, I added to the existing literature on the emissions impacts of real-time pricing using a superior dataset of marginal emission rates. Finally, I used these analyses to aid an exploration of the broader political economy of real-time pricing. In this chapter I briefly review the results of each inquiry and their relevance to policymakers; I close with proposals for further research.

## 8.1 Revenue Impacts on Intermittent Generators

In Chapters Four and Five I develop a method for evaluating the counterfactual wholesale market prices under RTP in the New England power market from 2003-2006. The model scope includes only the day-ahead power market, treats producer and system operator behavior as exogenous, and considers only within-hour price response with existing technologies. The data behind the model is publicly available from ISO-NE and includes the actual bids submitted to the day-ahead market and observed demand and prices. The simulation is described in detail in Chapter Four and summarized here in Figure 8-1.

The results of this simulation support the hypothesis that RTP will affect intermittent generators differently than the generation sector as a whole, but not in the way hypothesized in Chapter Two. Specifically, in the New England power market, intermittent generators

Figure 8-1: Summary: Market Simulation Model



**Steps 1 and 2 define the supply schedule as the cummulative offered quantities at each price**

| Bid Price | Bid Quantity | Cummulative Quantity |
|---|---|---|
| 18.10 | 100 | 100 |
| 18.90 | 25 | 125 |
| 21.00 | 25 | 150 |
| 21.05 | 250 | 400 |
| . | . | . |
| . | . | . |

**Step 3 identifies the flat wholesale clearing price**

**Step 4 defines the demand schedule, anchored by the observed retail equilibrium**

**Step 5 finds the RTP equilibrium as the intersection of supply and elastic demand**

In high demand hours, price and quantity decrease under RTP

In low demand hours, price and quantity increase under RTP may expect revenue losses due to RTP, but these losses will be comparatively less than the losses expected by the generation sector as a whole and much less than the losses faced by peak generators. This result applies to both the solar and wind sites which were considered and holds qualitatively across a number of sensitivity tests, as described in Chapters Four, Five, and Appendix C. For the base RTP scenarios with a moderate elasticity of -0.3, the four intermittent generators considered all face revenue losses of less than 5%, while the average generator expects losses of over 6% and peak generators over 55%. These results are summarized in Figure 8-2 and Table 8.1.

While the basis for this research was revenue, rather than profit, a note should be made that the same revenue loss will have different implications for different generation technologies. For renewables, hydro, and nuclear, which have close to zero marginal operating cost, a loss of revenue is translated almost entirely to a loss in profit. Coal, oil, and gas, which have significant marginal input costs (primarily fuel but also pollution permits and other costs), a unit loss in revenue may be halved or more when translated to profit loss.

## 8.2 Emissions Impacts

The model developed in Chapter Four evaluates hourly changes in quantity in addition to price. Using these changes, in Chapter Six I evaluate the counterfactual changes in emissions of $CO_2$, $SO_2$, and $NO_x$ which would have resulted from an RTP policy from 2003-2006. These changes are evaluated by multiplying the vector of hourly quantity changes by a vector of marginal emission rates of each pollutant. Hourly marginal emission rates were developed for the New England power market using EPA Continuous Emissions Monitoring data and a method which identifies those units that are responding to changes in load in any particular hour and calculates marginal rates as the average of all load-responsive emission rates. This method is documented in Chapter Six and, more thoroughly, elsewhere[14].

The results of this analysis support the hypothesis that RTP would cause small short-run reductions in emissions. Summing across the model period, with the moderate elasticity of -0.3, I find decreases of 2.4%, 1.6%, and 2.9% for $CO_2$, $SO_2$, and $NO_x$, respectively. These results, which are summarized in Table 8.2 and Figure 8-3, are consistent with previous

Table 8.1: Summary of Revenue Impacts on Intermittent Generators

| | | %Δ Revenue, RTP Compared to Flat | | |
|---|---|---|---|---|
| Year | Flat Revenue ($) | $\epsilon = -0.1$ | $\epsilon = -0.3$ | $\epsilon = -0.5$ |
| All Generation Sector | | | | |
| 2003 | 5.57B | -1.7 | -4.5 | -6.6 |
| 2004 | 6.71B | -3.0 | -7.2 | -10.2 |
| 2005 | 9.34B | -3.3 | -8.5 | -12.6 |
| 2006 | 7.40B | -1.5 | -4.0 | -6.0 |
| All Years | 29.02B | -2.5 | -6.3 | -9.2 |
| Hull Near-Shore Wind | | | | |
| 2003 | 127K | -1.1 | -2.9 | -4.4 |
| 2004 | 160K | -2.4 | -5.4 | -7.4 |
| 2005 | 205K | -1.5 | -4.0 | -6.0 |
| 2006 | 162K | -0.7 | -1.8 | -2.7 |
| All Years | 653K | -1.5 | -3.6 | -5.2 |
| Nantucket Off-Shore Wind | | | | |
| 2003 | 185K | -1.2 | -3.1 | -4.7 |
| 2004 | 205K | -2.4 | -5.4 | -7.5 |
| 2005 | 266K | -1.5 | -4.0 | -6.0 |
| 2006 | 211K | -0.6 | -1.6 | -2.5 |
| All Years | 868K | -1.4 | -3.6 | -5.2 |
| Northborough *in situ* Solar, incomplete data set | | | | |
| 2003 | 53K | -1.0 | -2.6 | -3.9 |
| 2004 - No Available Data | | | | |
| 2005 - No Available Data | | | | |
| 2006 | 70K | -1.1 | -2.6 | -3.8 |
| All Years | 123K | -1.0 | -2.6 | -3.8 |
| Worcester TMY Solar | | | | |
| 2003 | 63K | -0.6 | -1.7 | -2.6 |
| 2004 | 72K | -1.1 | -2.9 | -4.2 |
| 2005 | 104K | -1.5 | -3.8 | -5.7 |
| 2006 | 85K | -1.2 | -2.8 | -4.1 |
| All Years | 324K | -1.2 | -2.9 | -4.4 |

work on short-run emissions and RTP [22, 21]. Long-run emissions impacts are less certain, however. In Chapter Six I speculate that RTP may shift long-run marginal emission rates downwards, based on a comparison of the current marginal and average rates calculated from CEM data. This downward shift may actually incur private costs on future renewable generation investors, since the emissions savings they take credit for will decrease. The long-run effect of RTP on emissions, though, has not been studied in a rigorous way.

Table 8.2: Retrospective Emissions Changes from RTP, as a Percentage Change from Flat Emissions

| Panel A: $CO_2$ | 2003 | 2004 | 2005 | 2006 | Four-Year Total |
|---|---|---|---|---|---|
| Flat ($10^9$ kg) | 86 | 87 | 81 | 101 | 355 |
| $\epsilon$ = -0.1 | -0.5 | -1.0 | -1.5 | -0.5 | -0.9 |
| $\epsilon$ = -0.3 | -1.4 | -2.7 | -4.2 | -1.4 | -2.4 |
| $\epsilon$ = -0.5 | -2.1 | -4.1 | -6.3 | -2.2 | -3.6 |
| **Panel B: $SO_2$** | **2003** | **2004** | **2005** | **2006** | **Four-Year Total** |
| Flat ($10^6$ kg) | 236 | 229 | 209 | 285 | 958 |
| $\epsilon$ = -0.1 | -0.5 | -0.7 | -1.0 | -0.3 | -0.6 |
| $\epsilon$ = -0.3 | -1.3 | -1.8 | -2.8 | -1.0 | -1.6 |
| $\epsilon$ = -0.5 | -1.9 | -2.8 | -4.3 | -1.5 | -2.5 |
| **Panel C: $NO_x$** | **2003** | **2004** | **2005** | **2006** | **Four-Year Total** |
| Flat ($10^6$ kg) | 78 | 68 | 63 | 77 | 286 |
| $\epsilon$ = -0.1 | -0.8 | -1.1 | -1.9 | -0.6 | -1.1 |
| $\epsilon$ = -0.3 | -2.2 | -2.9 | -5.2 | -1.6 | -2.9 |
| $\epsilon$ = -0.5 | -3.3 | -4.4 | -7.9 | -2.4 | -4.3 |

## 8.3 Political Economy of Real-Time Pricing

In Chapter Seven I combined these economic and environmental results with a more general set of theories of behavior and political processes to explore how various participants in the policy discussion may come to support or oppose RTP policies.

I propose that consumers are unlikely to dedicate significant resources to supporting RTP even though they stand, on average, to gain. At the individual level, prospect theory suggests that, while RTP's net monetary benefits summed for all consumers are positive, the net utility benefits may be negative due to framing effects and the greater affect of losses relative to gains. In other words, the minority of consumers who lose from RTP are expected to be more motivated than the majority of consumers who gain. At the organizational level, consumers face a collective action dilemma – since all consumers may benefit from RTP regardless of whether they devote resources to support it, none would be expected to devote any resources to supporting the policy.

Producers, on the other hand, constitute a concentrated interest group which is likely to dedicate significant resources to oppose RTP. Ownership of generation assets in New England does not seem sufficiently segregated by class to create significant conflicts within the producer interest group. A policy of Hicksian compensation could in theory compensate any existing producers for their losses – in effect giving away any short-run benefits of RTP in order to secure the greater long-run benefits of more efficient investment signals. To be successful, such a policy would have to ensure confidence among producers in the government's ability to make long-term commitments (as generation assets may exist 40+ years), but a precedent for such compensatory payments has already been established in the form of stranded-cost payments in the restructuring process. This analysis helps explain why RTP, a welfare-improving policy, has not yet been implemented. To overcome these barriers will require at least a reframing of RTP for consumers, and probably a reliable commitment by the government to compensate producers who lose under RTP.

## 8.4 Relevance for Policymakers and Investors

The intended audience for this research consists of practitioners in the electricity policy and investment spheres. For these stakeholders, the most relevant results can be summarized as follows:

- In practice, RTP is not a technology-neutral policy. I have shown conclusively that RTP has differential revenue implications for different generation technologies. These revenue impacts, though, translate into inconclusive profit impacts, since some generators have a much higher fraction of fixed costs than others. For policymakers, this result highlights the need to craft coherent and systemic electricity policy, so that policies explicitly aimed at promoting one technology (for example, the Renewable Portfolio Standard) are not undermined by others (which may be the case with RTP).

For investors, this research demonstrates a method of forecasting the effects that RTP adoption would have on potential investments.

- RTP is not an emissions-neutral policy. In the New England power market, RTP is expected to reduce short-run emissions but may increase long-run emissions. The extent to which this increase counters other regulatory objectives should be considered in policy development.

## 8.5 Directions for Further Work

While this thesis is intended to be a thorough investigation of the environmental impacts of RTP (both directly, via emissions, and indirectly, via competitive impacts on renewable generators), a number of ideas for further investigation have arisen in the process of research. In this closing section, I highlight a few of these possible directions.

First - the choice of model form. I have developed a bid-based model from publicly-available data which is different from the input-cost-based models [21, 10] or dispatch simulation models used elsewhere. Each method makes a different tradeoff among complexity, amount of data, reliance on public versus proprietary data, model scope, and assumptions about producer behavior (and in particular market power). Future work could explore the implications of each of these tradeoffs in a more systematic way than I was able to do in this research.

Second - relaxing my assumptions about producer and system operator behavior. Models with endogenous producer and system operator decisions have not, to my knowledge, been used to analyze the potential effects of RTP. I have not attempted to consider what value such models might add, but future researchers may explore this possibility and, if promising, develop such a model.

Third - relaxing my assumptions about the scope of consumer response. I have limited this analysis to consider within-hour, short-run price response by consumers. A consideration of intra-hour substitution, including the diffusion of new technologies, may add value to evaluating long-run effects. A useful starting point would be the dynamic model developed by Black [4].

Fourth - the long-run emissions effects of RTP. To my knowledge this important impact has not been studied. Such an analysis could start with Borenstein and Holland's long-run model [10, 6] and develop an emissions profile for their equilibrium generation mix based on observed emission rates of new plants.

Finally - an analysis of how RTP interacts with other electricity policies in the long-run. I have not considered in any rigorous way how the effects of RTP may interact (synergistically or antagonistically) with other current or proposed electric-sector policies. Specifically, long-run interaction with new emissions regulations (such as a carbon tax or cap-and-trade system), renewable energy policies (such as the Renewable Portfolio Standards adopted in all New England states or the renewable feed-in tariffs currently discussed), and economic policies (such as continuing deregulation/restructuring or decoupling) will be important to consider in developing a coherent set of electricity policies.

Figure 8-2: Summary: Changes in Annual Revenue Due to RTP

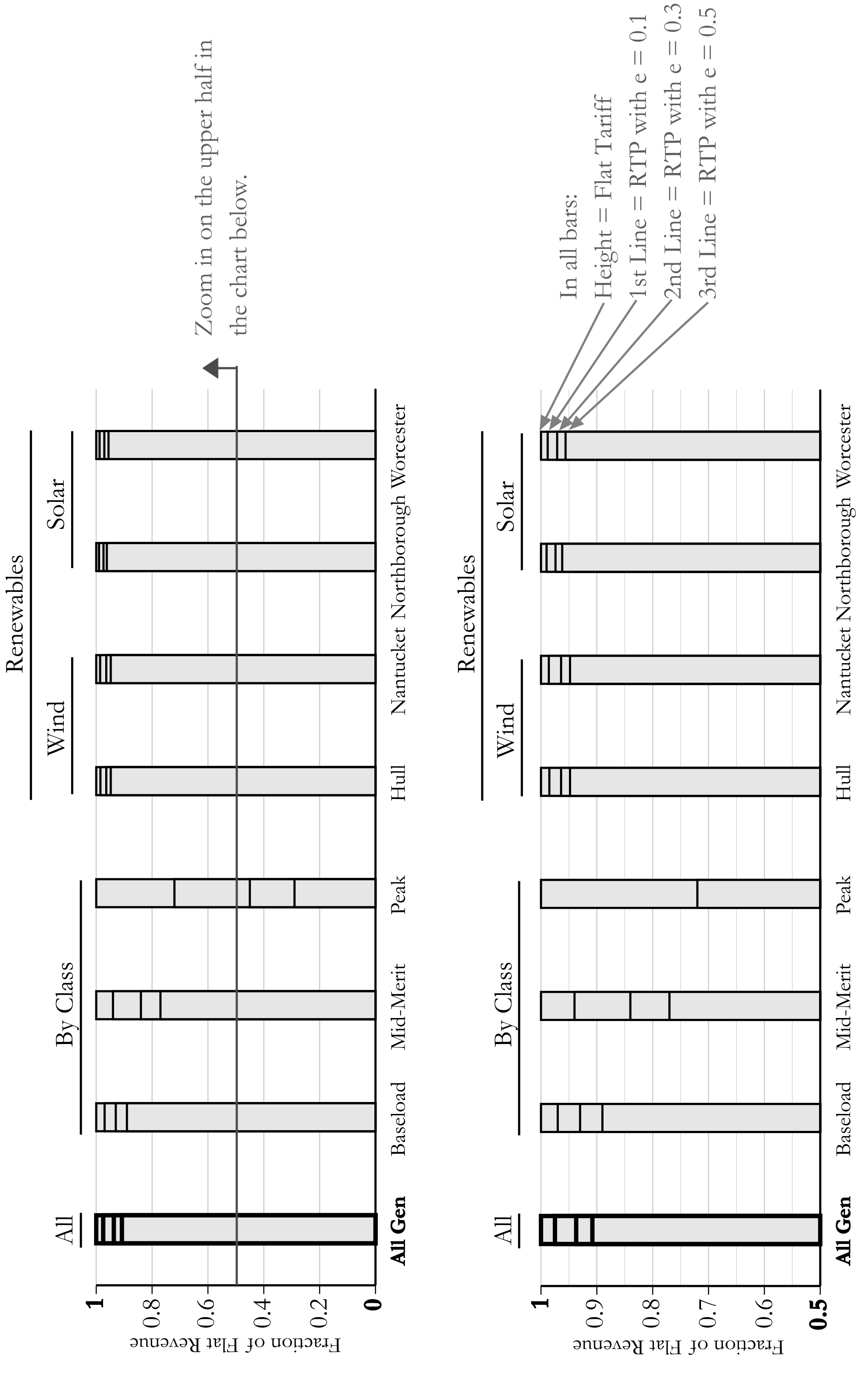
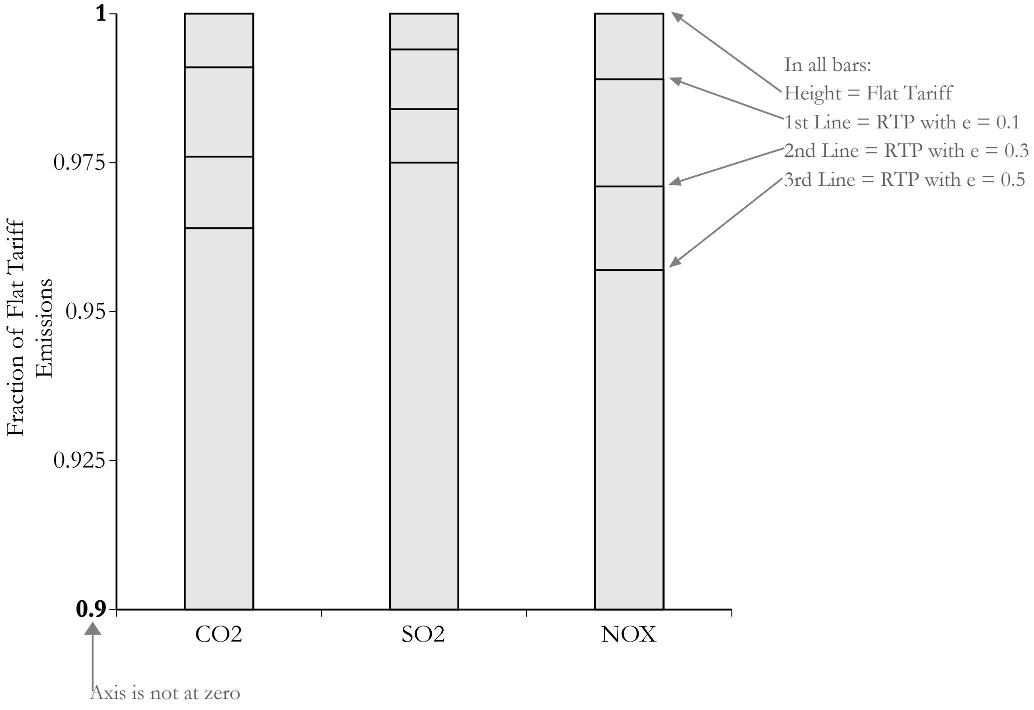


Figure 8-3: Summary Change in Emissions Due to RTP



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# Appendix A

# Data Structure and Documentation

Simulations and analyses throughout this thesis were based on a database built from a variety of sources. The database was built in MySQL and consists of a number of tables, the structure and sources of which are documented below. Not all data included in this database was used in the simulations described in this thesis — I document the complete set here in the hope that others will find this database useful for other analyses.

## A.1 Bid_Header Table

### Summary

The Bid_Header table stores hourly bid information submitted to the ISO-NE day-ahead market, except the energy bid component (because multiple energy blocks are bid for each asset in each hour). There is one record for each generation asset for each hour – therefore the combination of the datetimeDLS, participant_ID, and asset_ID fields is unique for each record. The source for all data is the ISO-NE Day-Ahead Bid Data [17] unless otherwise noted.

### Data Management

Bids are available from the ISO-NE website [17] in separate comma-separated text files for each day. The SiteSucker program was used to automate the download of all bid files from

1999 to 2006 (approximately 2800 files). A script written in Pearl (and included in Appendix B) read the unique hourly data into a tab-delimited text file for import into the Bid_Headers table using the 'insert into' command in MySQL.

## Fields and Descriptions

- **BidHeader_ID:** An 11-digit primary key for this table, assigned by me in the script which reads the daily ISO-NE files into a single table and not from ISO-NE. The field simply provides a unique ID for each record in the table.
- **date_time:** Date and time indicated in the ISO-NE table, formatted as YYYYMMDDHH. Note that on nights when daylight savings time begins and the 2 AM hour is repeated, both hours are marked with the same timestamp in this field.
- **participant_ID:** An anonymous ID number assigned to the market participant by the ISO, consistent across hours. Participants may own many assets. Designated "Masked Lead Participant ID" in ISO documents.
- **asset_ID:** An anonymous ID number assigned to the asset by the ISO, consistent across hours. Designated "Masked Asset ID" in ISO documents.
- **MustTakeE:** From ISO documentation – "The Amount of energy self-scheduled by the Participant in the hour from this resource" (MW). Designated "Must Take Energy" in ISO documents.
- **EconMaxE:** The asset's maximum output in non-emergency situations (MW). Designated "Economic Maximum" in ISO documents.
- **EconMinE:** The asset's minimum non-zero output in non-emergency situations (MW). Designated "Economic Minimum" in ISO documents.
- **ColdPrice:** Price that must be paid to start the asset from a cold state ($). Designated "Cold Startup Price" in ISO documents.
- **InterPrice:** Price that must be paid to start the asset from an intermediate state ($). Designated "Intermediate Startup Price" in ISO documents.

- **HotPrice:** Price that must be paid to start the asset from a hot state ($). Designated "Hot Startup Price" in ISO documents.

- **NoLoadPrice:** Price that must be paid to use the asset in any condition, excluding start-up and marginal energy costs ($). Designated "No Load Price" in ISO documents.

- **datetimeDLS:** Datetime field as above, but with an 11th digit added which takes the value of 1 in the repeated 2 AM hour when daylight savings time begins and 0 otherwise. Format is therefore YYYYMMDDHHX where X is "1" in the repeated 2AM hour, "0" otherwise.

## A.2 Bids Table

### Summary

The Bids table stores the energy component of the hourly bids submitted to the ISO-NE day-ahead market. There is more than one record for each generation asset for each hour if that asset submitted a multipart bid. The combination of datetimeDLS, participant_ID, asset_ID, and block_number is therefore unique. The source for all data is the ISO-NE Day-Ahead Bid Data [17] unless otherwise noted.

### Data Management

Bids are available from the ISO-NE website [17] in separate comma-separated text files for each day. The SiteSucker program was used to automate the download of all bid files from 1999 to 2006 (approximately 2800 files). A script written in Pearl (and included in Appendix B) read the hourly multi-part bids into a tab-delimitted text file for import into the Bids table using the 'insert into' command in MySQL.

### Fields and Descriptions

- **Bid_ID:** An 11-digit primary key for this table, assigned by me in the script which reads the daily ISO-NE files into a single table and not from ISO-NE. The field simply provides a unique ID for each record in the table.

- **date_time:** See datetime field in Bid_Headers table.
- **participant_ID:** See participant_ID field in Bid_Headers table.
- **asset_ID:** See asset_ID field in Bid_Headers table.
- **block_number:** A number from 1 to 10. Block numbers are assigned to the parts (or blacks) of a multi-part bid in ascending order of price. Corresponds to the block number in the ISO-NE tables.
- **bid_amount:** Quantity offered in the bid, in MW. Corresponds to the “Energy” field in ISO-NE tables.
- **bid_price:** Price of energy offered in the bid, in $/MWH. Corresponds to the “Price” field in ISO-NE tables.
- **datetimeDLS:** See datetimeDLS field in Bid_Headers table.

## A.3 reg_data table

### Summary

This table contains an assortment of hourly data from various sources. The table contains most data I gathered *besides* bid data and resource data.

### Data Management

Data was gathered from a variety of sources as documented below. All sources indicated the date and hour of the reported observation. MySQL insert statements were used to match the observation’s timestamp with the correct record and add data to the table.

## Fields and Descriptions

- **YEAR:** Year, formated as YYYY.
- **MON:** Month, formatted as MM.
- **DAY:** Day, formatted as DD.
- **HOUR:** Hour, formatted as HH.
- **ISO_LOAD:** The total NEPOOL system load, in MW, reported by the ISO for the period 1999 to 2003 and downloaded from the ISO's "Hourly Historical Data Post-Market" webpage [18].
- **DRY_BULB:** From ISO Documentation – "the New England (weighted average of 8 weather stations) dry bulb temperature in degrees Fahrenheit." Downloaded from the ISO's "Hourly Historical Data Post-Market" webpage [18].
- **ENERGY_PR:** Clearing price for energy sold in that hour, in $/MWH and available from 1999 to 2003. Downloaded from the ISO's "Hourly Historical Data Post-Market" webpage [18].
- **DA_DEMD:** From ISO documentation – "day-ahead demand consists of fixed and price sensitive demand bids plus decrement bids & increment offers." This is the "DA_DEMD" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19]. Units are MWH.
- **DEMAND:** Total NEPOOL system demand, in MWH. This is the "DEMAND" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19].
- **DA_LMP:** Day ahead locational marginal price at the NEPOOL hub, in $/MWH. This is the "DA_LMP" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19].

- **DA_EC:** Day ahead energy component of the locational marginal price at the NEPOOL hub, in $/MWH. This is the "DA_EC" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19]. The difference between LMP and EC is the congestion component of the locational marginal price. For details on locational marginal pricing see Stoft [40].

- **RT_LMP:** Real-time locational marginal price at the NEPOOL hub, in $/MWH. This is the "RT_LMP" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19].

- **RT_EC:** Real-time energy component of the locational marginal price at the NEPOOL hub, in $/MWH. This is the "RT_EC" field for NEPOOL in the Hourly SMD Data spreadsheets available on the ISO's "Hourly Zonal Information" webpage [19]. The difference between LMP and EC is the congestion component of the locational marginal price. For details on locational marginal pricing see Stoft [40].

- **NG_MA_Commercial:** Price of natural gas for commercial customers in Massachusetts, in Dollars per Thousand Cubic Feet. Reported monthly by the US Energy Information Administration and downloaded from their website[33].

- **Oil_NO2Diesel_NYH:** New York Harbor Number 2 Heating Oil spot price. Reported daily by the US Energy Information Administration and downloaded from their website[32].

- **ElPr_AvRt:** Average retail price of electricity in New England, in $/MWH. This is calculated as the average of the state retail prices, weighted by electricity use, monthly. State data used for this calculation is reported monthly by the US Energy Information Administration and was downloaded from their website [34].

- **CO2:** Marginal emissions rate of $CO_2$ in New England, in tons/MWH. Calculated using EPA Continuous Emissions Monitoring data as documented in Chapter 6 and [14].

- **SO2:** Marginal emissions rate of $SO_2$ in New England, in tons/MWH. Calculated using EPA Continuous Emissions Monitoring data as documented in Chapter 6 and [14].
- **NOX:** Marginal emissions rate of $NO_x$ in New England, in tons/MWH. Calculated using EPA Continuous Emissions Monitoring data as documented in Chapter 6 and [14].
- **Weekday:** An integer from 1 to 7 corresponding to day of week. 1 = Sunday through 7 = Saturday.
- **Month_Flag:** Can be used to flag seasons or name months. No current use.
- **installed_cap:** Installed capacity in NEPOOL, reported daily by ISO-NE in MW. Downloaded in ISO NE's "Daily Capacity Status" spreadsheet[20].
- **avail_cap:** Available capacity in NEPOOL, reported daily by ISO-NE in MW. Downloaded in ISO NE's "Daily Capacity Status" spreadsheet[20]. The available capacity is the total installed capacity less any outages and units which are unavailable due to start time.
- **datetimeDLS:** As above.

## A.4 Resource Tables

For each resource considered in the thesis, I assembled a table with records for each hour, consisting of a timestamp and the generation from that resource during the hour. The sources of this information are documented in Chapter 6.

## A.5 Bid Text Files

One input to the algorithm documented in Appendix B is a set of text files containing all bids for a given hour. These text files are named with their 'datetimeDLS' timestamp, i.e. "YYYYMMDDHHX.txt" where X = 1 for the repeated 2AM hour on the night when daylight savings time begins and 0 otherwise. The contents of the text file are simply two tab-separated columns, Price and Quantity. Quantity represents the marginal quantity offered at that price, not the cumulative quantity offered at that or lower prices, and it may be the sum of bids from multiple assets at that price.

# Appendix B

# Scripts

## B.1 Wholesale Market Simulation

```
##################################################################
##RTP_Simulation.pl
##Script written by JP Connolly
##1 June 2007
##
##This will implement the RTP sim by reading in text files with bid
##   data and finding a new market equilibrium
##################################################################
# Basic requirements:
#   Check the script below and make sure the elasticity and file
#      paths are correct
#   Need Monthly and Hourly Input files - see below for where/what
#      they should be
#   Need a folder ~/Input/ containing the properly named and
#      formatted bid tables for each hour
#      Names - should be datetimeDLS.txt, i.e. 'YYYYMMDDHHX.txt'
#            where 'X' is 1 for the repeated 2AM hour when
#            daylight savings time begins, 0 o/w
#      Format - 2 columns, tab delimited text file. first column
#            is price in dollars/mwh second collumn is the quantity
#            offered at that price (not the cummulative quantity)
##################################################################


########################################
### Get parameter values and inputs    ###
########################################


###  First get a name for the output file  ####
```

```
print "Please enter the name for this run (No Spaces) and hit return.\n";
my $run_name = <STDIN>;
chomp($run_name);
my $run_name_out = $run_name."_Out.txt";
my $run_name_report = $run_name."_Report.txt";
print "Thank you.\n";
###  You’re welcome  ############################


###  Now define some parameters  ################
my $price_elasticity = -.5;       #inter-hour price elasticity
my %t_and_d_costs = ();            #we’ll get this from the input file

### If you want, define classes of consumers and their elasticities
### You would have to make some changes to the script below to make
###       this functional
### Right now, different classes is not implemented
my @classes = (’retail’, ’commercial’,’industrial’);
my %class_fractions = ();
#my %class_elasticities = (
#   retail => -.35,
#   commercial => -.2,
#   industrial => -.2);

my $TandD_Multiplier = 1.00;
###Can use this to test sens. to perturbations in TandD costs




#######################################################################
##   Get Monthly inputs                                              ##
##                                                                   ##
## Open the monthly input file, containing prices and class shares   ##
##    by month.                                                      ##
## Note that these are not currently used and this section could be  ##
##    simplified                                                     ##
#######################################################################

my $monthly_data_file = "/InputData/MonthlyData.txt";
open(DAT, "$monthly_data_file") || die("Could not open $hourly_file!");
@filecontents = <DAT>;
close(DAT);

my $year_month;
my $retail_price;
my $commercial_price;
my $industrial_price;
my $t_and_d_cost;


my $retail_fraction;
my $commercial_fraction;
my $industrial_fraction;
```

```
my %end_use_prices = ();
my %avg_prices = ();

foreach $record (@filecontents)
{

   ($year_month, $retail_price, $commercial_price, $industrial_price,
      $t_and_d_cost, $retail_fraction, $commercial_fraction,
      $industrial_fraction) = split(/,/ , $record);
   $end_use_prices{$year_month}{'retail'} = $retail_price;
   $end_use_prices{$year_month}{'commercial'} = $commercial_price;
   $end_use_prices{$year_month}{'industrial'} = $industrial_price;
   $t_and_d_costs{$year_month} = $t_and_d_cost;
   $class_fractions{$year_month}{'retail'} = $retail_fraction;
   $class_fractions{$year_month}{'commercial'} = $commercial_fraction;
   $class_fractions{$year_month}{'industrial'} = $industrial_fraction;
   $avg_prices{$year_month} = $retail_price*$retail_fraction +
                              $commercial_price*$commercial_fraction +
                              $industrial_price*$industrial_fraction;
}

#####  Done getting all the monthly data  ############################




######################################################################
### Get hourly inputs                                              ##
###                                                                ##
### Now we need to grab hourly info like the observed demand,      ##
### the retail price, the observed clearing price, etc....         ##
### we will put those values in hashes identified by the datetime  ##
###    for retrieval later                                         ##
### This is the reason that the bid tables are named by datetimeDLS ##
######################################################################
my $hourly_file = "/InputData/HourlyData.txt";
open(DAT, "$hourly_file") || die("Could not open $hourly_file!");
@filecontents = <DAT>;
close(DAT);

my $datetime;
my $observed_load;
my $observed_retail_price;
my $observed_EC;

my %observed_loads = ();
my %LoadsByClass = ();
my %hourly_factors = ();
my %observed_ECs = ();

foreach $record (@filecontents)
{
```

```
   ($datetime, $observed_load, $observed_retail_price, $observed_EC)
         = split(/,/ , $record);

   $observed_loads{$datetime} = $observed_load;
   $observed_ECs{$datetime} = $observed_EC;
   $year_month = substr($datetime, 0, 6);


   ### Calculate hourly factors following Borenstein and Holland...
   ###Avoid div by zero below by setting zeros to 1.
   $hourly_factors{$datetime} = ($observed_loads{$datetime}) /
                     ($avg_prices{$year_month} ** $price_elasticity);

      if ($hourly_factors{$datetime} == 0)
      {
         $hourly_factors{$datetime} = 1;
      }
}

####  Done getting hourly input data (except the bids of course)  ####



### Now that we have that hourly data we can dive into the bids ###

my $path = "/Input";
my @filecontents;


###Read each file name in the directory into an array########
opendir(DIR, $path) || die "\nCouldn’t open $path.
                       Ensure that directory exists correctly: $!";
my @files = readdir(DIR);
@files = reverse(@files);
pop(@files);
pop(@files);
pop(@files);
@files = reverse(@files);
### Done reading all the file names######################

### The RTP_Output will have the hourly simulate output
### Here we just open it up and write the header

open(RTP_Output, ">>/Output/$run_name_out") ||
                        die("Could not open Output file");

print RTP_Output "datetime\tobs_ld\tobs_EC\tFlatCP
                   \tRTPEqPr\tRTPEqQ\tTandDCosts";

print RTP_Output "\n";



### The RTP_Report will be an automatic documentation of the run
```

```
### Here we write the run name and input parameters

open(RTP_Report, ">>/Output/$run_name_report")||
                        die("Could not open Report");
print RTP_Report "Run Name:  $run_name\nClass Elasticities:\n";
print RTP_Report "T and D Multiplier:  $TandD_Multiplier\n";







#############################################################
## And now, the solution algorithm                          #
##                                                          #
## Nothing fancy, just read the inputs and find the         #
##    intersection of two curves                            #
#############################################################

foreach $file (@files)      #Loop through the bid files
                            #in the input directory
{

   open(DAT, "$path/$file") || die("Could not open $path/$file!");
   @filecontents = <DAT>;
   close(DAT);

   #get date
   my $datetime = $file;
   chop($datetime);
   chop($datetime);
   chop($datetime);
   chop($datetime);
   print "$file\n";
   ### print "$datetime\n";

   if ($observed_loads{$datetime} != 0)
   {


      my $n = 0;
      my @PriceArray;
      my @QuantArray;
      my @CummQuantArray;
      my $bid_price;
      my $bid_quantitiy;
      my $FoundCP = 0;
      my $FlatClearingBid;
      my $CurrentBidID;
      my $SupplyCurvePrice;
      my $CurrentQuantity;
```

```
my $TotalDemandCurveQuantity;
my $ClassDemandCurveQuantity;
my $FoundRTPEquilibrium = 0;
my $EquilibriumDirection = 0;
my $QuantDif;
my $EndUseMinusTandD;
my $year_month = substr($datetime,0,6);


$observed_load = $observed_loads{$datetime};
$observed_EC = $observed_ECs{$datetime};
chomp($observed_EC);


### First find the clearing price for the observed demand,
###  and load the bids into an array

foreach $record (@filecontents)
{

   ### print "$record";
   ($Price, $Quantity) = split(/\t/ , $record);

   ### print "Price = $Price     Q = $Quantity";

   $PriceArray[$n] = $Price + $t_and_d_costs{$year_month};
   $QuantArray[$n] = $Quantity;
   $CummQuantArray[$n] = $CummQuantArray[$n - 1] + $Quantity;

   if (($FoundCP == 0) && ($CummQuantArray[$n] >= $observed_load))
   {
      $FoundCP = 1;
      $FlatCP = $Price;
      $FlatClearingBid = $n;
   }

   $n = $n + 1;
}

my $totalbids = n;



### Now search for the RTP Equilibrium - basically I start at
### the lowest bid and look to see if the demand at that bid's
### price would be met by the cummulative quantity.
###      If yes, we have found the equilibrium
###      If not, go to the next bid

$CurrentBidID = $FlatClearingBid;
$CurrentPrice = $PriceArray[$CurrentBidID];
$SupplyCurveQuantity = $CummQuantArray[$CurrentBidID];
```

```
$DemandCurveQuantity = 0;
$TotalDemandCurveQuantity =($hourly_factors{$datetime} *
                     ($CurrentPrice ** $price_elasticity));


if ($TotalDemandCurveQuantity > $SupplyCurveQuantity)
{
   $FoundRTPEquilibrium = 0;
   $EquilibriumDirection = 1;
}
elsif ($TotalDemandCurveQuantity < $SupplyCurveQuantity)
{
   $FoundRTPEquilibrium = 0;
   $EquilibriumDirection = -1;
}
else
{
   $FoundRTPEquilibrium = 1;
}


while ($FoundRTPEquilibrium == 0)
{
   $CurrentBidID = $CurrentBidID + $EquilibriumDirection;
   $CurrentPrice = $PriceArray[$CurrentBidID];
   $SupplyCurveQuantity = $CummQuantArray[$CurrentBidID];

   $TotalDemandCurveQuantity = 0;
      $TotalDemandCurveQuantity = ($hourly_factors{$datetime}
                          * ($CurrentPrice ** $price_elasticity));

   $QuantDif = ($SupplyCurveQuantity - $TotalDemandCurveQuantity)
                                * $EquilibriumDirection;

   if ($QuantDif > 0)
   {
      $FoundRTPEquilibrium = 1;
      if ($EquilibriumDirection == -1)
      {
         $CurrentBidID = $CurrentBidID + 1;
      }
   }

   if ($CurrentBidID == 0 or $CurrentBidID   == $totalbids)
   {
      print "Could not find solution for hour ".$hour[0]."\n";
      $FoundRTPEquilibrium = 1;
   }
}


### store the new quantity and write out what we’ve learned
my $RTPEquilibriumPrice = $PriceArray[$CurrentBidID] -
                            $t_and_d_costs{$year_month};
```

```
      my $RTPEquilibriumQuantity = $TotalDemandCurveQuantity;
      my $TandD = $t_and_d_costs{$year_month};


      print RTP_Output "$datetime\t$observed_load\t$observed_EC
               \t$FlatCP\t$RTPEquilibriumPrice\t$RTPEquilibriumQuantity
               \t$t_and_d_costs{$year_month}";

      print RTP_Output "\n";

   } ### End if exixts

}  ### End For Each File loop

close (RTP_Output);
```

## B.2 Read ISO NE Files

```
##################################################################
##ISOParse.pl
##JP Connolly
##6 August 2007
##This should read the ISO bid csv's, parse the files,
##and convert them into a table for insert to sql
##################################################################

my $path = "/tmp/TestSQLOut.txt";

#Open Text files to write to later, these are the data tables that will
#be imported by sql

open(BidHeader, ">>/Output/TEstRun.txt") ||
                     die("Could not open BidHeader");

open(DAT, "$path") || die("Could not open $file!");
@filecontents = <DAT>;
close(DAT);

# Get date and dump the rest of the header

my $date;
# $date = substr(@filecontents[1], 19, 8);
$date = substr(@filecontents[1], 12, 8);
@filecontents = reverse(@filecontents);
pop(@filecontents);
pop(@filecontents);
pop(@filecontents);
pop(@filecontents);
pop(@filecontents);
```

```
@filecontents = reverse(@filecontents);
pop(@filecontents);

#loop through records in each file to write inserts

foreach $record (@filecontents)
{

my $record_type;
my $hour;
my $datetime;
my $PartID;
my $AssetID;
my $MustTakeE;
my $MaxEAvail;
my $EconMaxE;
my $EconMinE;
# my $ColdPrice;
# my $InterPrice;
# my $HotPrice;
# my $NoLoadPrice;
my $block1E;
my $block1P;
my $block2E;
my $block2P;
my $block3E;
my $block3P;
my $block4E;
my $block4P;
my $block5E;
my $block5P;
my $block6E;
my $block6P;
my $block7E;
my $block7P;
my $block8E;
my $block8P;
my $block9E;
my $block9P;
my $block10E;
my $block10P;
my @BidEnergy;
my @BidPrice;

($record_type, $hour, $PartID, $AssetID, $MustTakeE, $MaxEAvail,
    $EconMaxE, $EconMinE,
# $ColdPrice, $InterPrice, $HotPrice, $NoLoadPrice,
# $ColdPrice, $HotPrice, $NoLoadPrice,
$block1E, $block1P,
$block2E, $block2P,
$block3E, $block3P,
$block4E, $block4P,
$block5E, $block5P,
$block6E, $block6P,
```

```
$block7E, $block7P,
$block8E, $block8P,
$block9E, $block9P,
$block10E, $block10P) = split(/,/ , $record);

# print $hour;
#format the hour field
# if ($hour =~ /^"02X?"$/)
# {
#
# if ($hour =~ /^"02"$/)
# {
# $hour = "01";
# }
#
# if ($hour =~ /^"02X"$/)  #this is to catch the repeated daylight
#                         # savings hour, which is labeled '02X' in the ISO data
# {
# $hour = "02";
# }

# if ($hour < 10)
# {
# $hour = "0".$hour;
# print "$hour\n";
# }

$hour = substr($hour,1,2);

#create new vars to be used below
$datetime = $date.$hour;
@BidEnergy = ($block1E, $block2E, $block3E, $block4E, $block5E,
              $block6E, $block7E, $block8E, $block9E, $block10E);
@BidPrice =  ($block1P, $block2P, $block3P, $block4P, $block5P,
              $block6P, $block7P, $block8P, $block9P, $block10P);

#deal with the null asset IDs, just labeling them x100##,
#a tag that is different for each hour and should basically
#mean "null"

#now that we have the data in variables, let's write the text
#files to be used in the mysql load data
#
#I need two tables - one for bid header and one for the
#individual bids

$uniqueid = $uniqueid + 1;

## For most recent dates
# print BidHeader "$tableid$uniqueid\t$date$hour\t$PartID
#             \t$AssetID\t$MustTakeE\t$MaxEAvail\t$EconMaxE\t$EconMinE
#             \t$ColdPrice\t$InterPrice\t$HotPrice\t$NoLoadPrice\n";

##For 2001 - 2003 data (unsure about exact dates - double check)
```

```
# print BidHeader "$tableid$uniqueid\t$date$hour\t$PartID
#            \t$AssetID\t$MustTakeE\t$MaxEAvail\t$EconMaxE\t$EconMinE
#            \t$ColdPrice\t\t$HotPrice\t$NoLoadPrice\n";
##For pre 2001 data (and some early 2001 I think)
print BidHeader "$tableid$uniqueid\t$date$hour\t$PartID
     \t$AssetID\t$MustTakeE\t$MaxEAvail\t$EconMaxE\t$EconMinE
     \t\t\t\t\t\t$date$hour"."0"."\n";

$block_number = 0;

foreach $Block (@BidEnergy)
{

if (@BidEnergy[$block_number] > 0)
{
$uniqueid = $uniqueid + 1;

if ($block_number != 9)
{
                   print Bids "$BidTableID$uniqueid\t$date$hour
                   \t$PartID\t$AssetID\t$block_number\t@BidEnergy
                   [$block_number]\t@BidPrice[$block_number]\t
                   \t$date$hour"."0"."\n";
}

if ($block_number == 9)
{
chomp(@BidPrice[$block_number]);
print Bids "$BidTableID$uniqueid\t$date$hour
\t$PartID\t$AssetID\t$block_number\t@BidEnergy
[$block_number]\t@BidPrice[$block_number]\t
\t$date$hour"."0\n";
}
}

$block_number = $block_number + 1;
}
#}
}
}

close (BidHeader);
close (Bids);
```

# Appendix C

# Sensitivity Tests

A number of simulations were run with a range of input parameters in order to develop some intuition of how sensitive the model results are to univariate perturbations in the inputs. In the following sections I discuss the sensitivity of my conclusions with respect to non-generation costs, day-ahead demand shocks, and the exercise of market power.

## C.1 Non-Generation Costs

For each elasticity level, non-generation costs (NGC) of \$60, \$67.5, \$75, \$82.5, and \$90 were used as inputs — these runs are summarized in the boxplots in Figures C-1 and C-2[1]. For all elasticities at all NGC levels, the price and load distributions were compressed as expected. Mean price and load also decreased with RTP, except in the case of \$60/MWH NGC, which resulted in increased mean load. This indicates that the \$60/MWH non-generation cost is too low over the modeled period - it makes the total cost of power in RTP scenarios lower in most hours and therefore induces greater demand in most hours.

---

[1] *Boxplots* are used to show the distribution of a set of numbers. Values are plotted along the vertical axis. The box encompasses the 25th to 75th percentiles of distribution. The bold line inside the box denotes the median (i.e. 50th percentile) while the tails below and above the box show the min and max, respectively

## C.2 Day-Ahead Demand Shocks

The final panels in Figures C-1 and C-2 hold elasticity and NGC constant and amplifies the hourly demand by a factor of 0.95 and 1.05. These scenarios are meant to represent the possibility that introducing RTP may shift the fraction of load which clears in the day-ahead vs. the spot market, though the scenarios could also represent demand shocks due to other causes. While the means of both price and quantity vary predictably, the results are qualitatively similar to the base runs, with more compression of both price and quantity at lower load.

## C.3 Market Power

Generators could exercise market power in one of two ways – they could withhold capacity (by reducing the quantity that they bid into the wholesale market) or raise prices (by increasing the price that they bid into the wholesale market above their marginal cost). In order to model these effects, I simply add a multiplier which adjusts each bid price or quantity up or down, according to the scenario. Table C.1 describes four scenarios of how changes in the ability to exercise market power can be included in the model, and Table C.2 reports the results of each scenario. Note that, based on the discussions in Chapters 2 and 3, we expect RTP to reduce the ability of generators to exercise market power (or to reduce the incentives for doing so). Scenarios 2 and 3 are therefore more likely to be realistic. In all scenarios (including the Base RTP, which has no price or quantity adjustment), elasticity is -0.3.

In all cases the change has a significant effect on revenues compared to the Base RTP case, as expected. Of more interest are the relative effects of RTP on renewable vs. non-renewable generators. These relative impacts are qualitatively similar across all market power scenarios – specifically, both wind and solar generators are somewhat better off than the generation sector as a whole. When the generation sector loses revenue due to RTP, renewables lose somewhat less, and when the generation sector gains revenue due to RTP (due to their increased ability to exercise market power in this scenario), renewable generators gain somewhat more. While the producer behavior in this simulation is not sophisticated, the

Table C.1: Scenarios Considered in Market Power Sensitivity Tests

| Scenario | Treatment | Behavioral Interpretation |
|---|---|---|
| 1 | Increase prices in all bids by 10% | RTP increases the ability of generators to exercise market power through price adjustments. They take advantage by adding a 10% markup to their observed bid. |
| 2 | Decrease prices in all bids by 10% | RTP removes the existing ability of generators to exercise market power, which they had been exercising via price markups. They respond by removing a 10% non-competitive markup from their observed bid. |
| 3 | Increase quantities in all bids by 10% | RTP removes the existing ability of generators to exercise market power, which they had been exercising by withholding capacity. They respond by bidding in 10% more capacity than their observed bid. |
| 4 | Decrease quantities in all bids by 10% | RTP increases the ability of generators to exercise market power by withholding capacity. They take advantage by withholding 10% of capacity from their observed bid. |

results provide some support for the hypothesis that my conclusions regarding the differential impact of RTP on renewable generators are valid even if RTP changes the ability of generators to exercise market power.

Figure C-1: Simulated Load Distributions

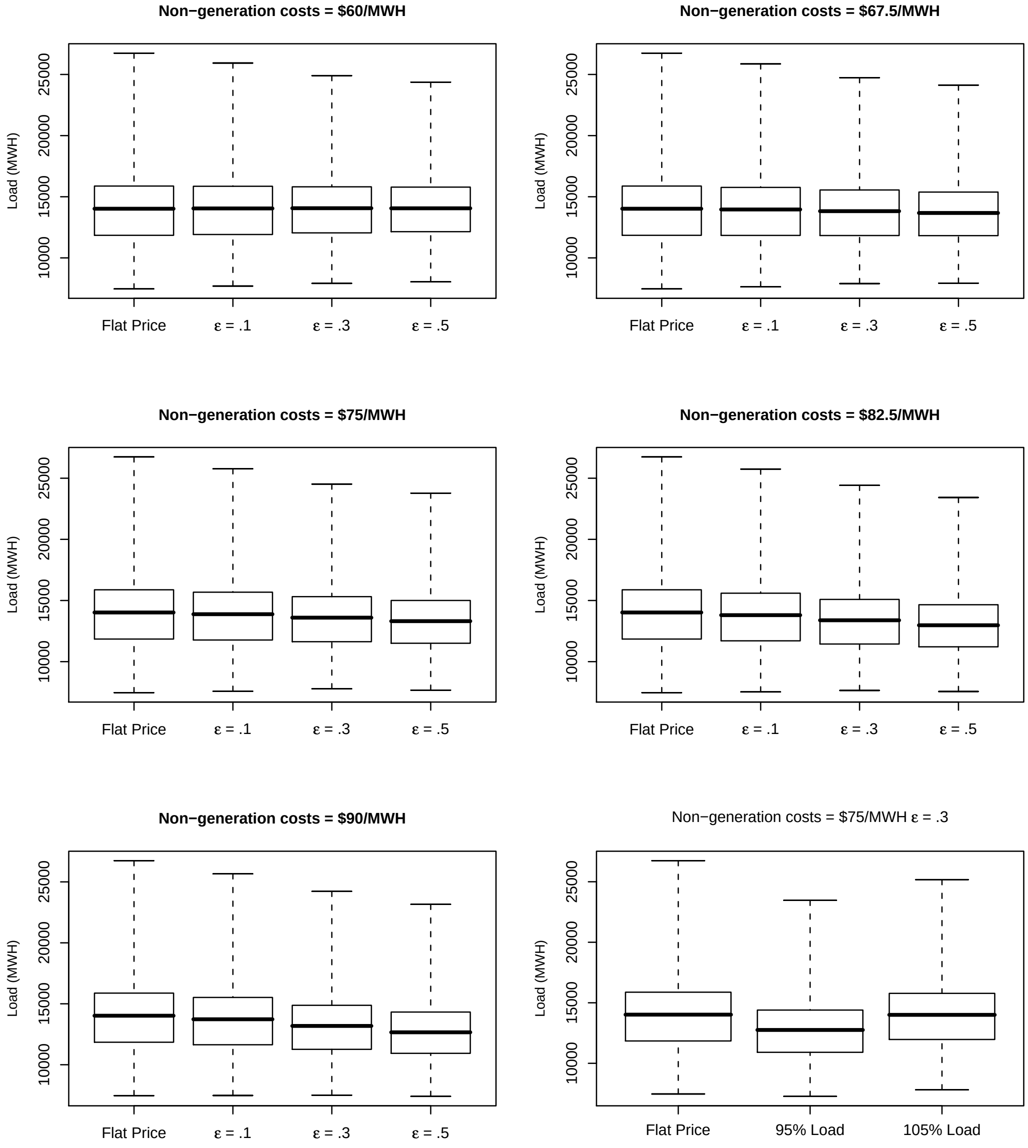

Figure C-2: Simulated Price Distributions

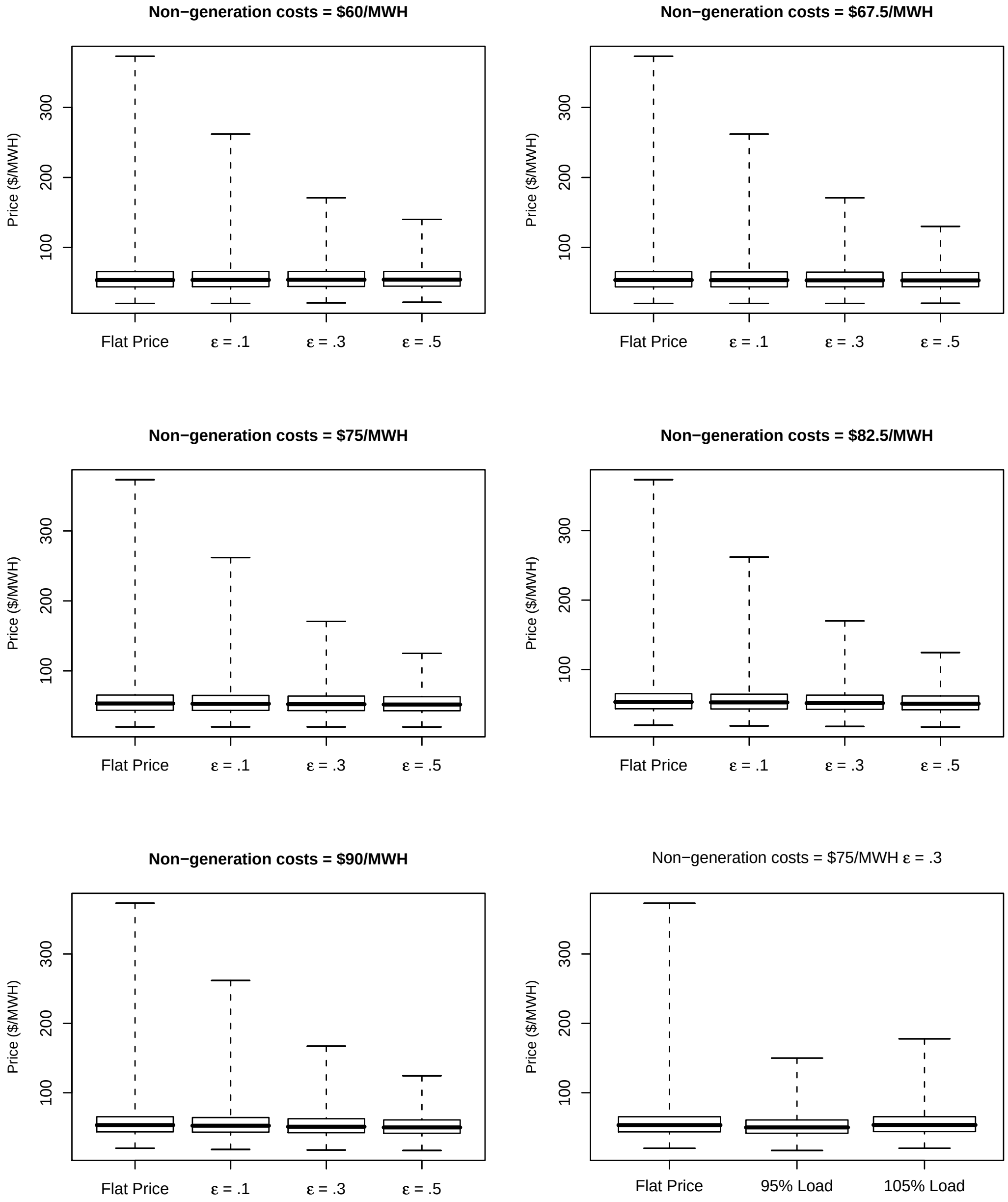

Table C.2: Summary: Market Power Sensitivity Tests

| | | | Bid Price | | Bid Quantity | |
|---|---|---|---|---|---|---|
| Scenario: | Flat Tariff | Base RTP | x1.1 | x0.9 | x1.1 | x0.9 |
| **Revenue** | | | | | | |
| All Gen($B) | 29.0 | 27.2 | 29.3 | 25.0 | 25.7 | 29.0 |
| $\Delta$ | | -6.3% | 0.9% | -13.7% | -11.4% | 0.1% |
| Hull ($K/MWi) | 653 | 630 | 686 | 572 | 589 | 680 |
| $\Delta$ | | -3.6% | 5.1% | -12.3% | -9.8% | 4.1% |
| Nantucket ($K/MWi) | 868 | 837 | 912 | 761 | 782 | 903 |
| $\Delta$ | | -3.6% | 5.1% | -12.3% | -9.9% | 4.0% |
| Northborough ($K/MWi) | 859 | 837 | 912 | 761 | 780 | 912 |
| $\Delta$ | | -2.6% | 6.2% | -11.4% | -9.1% | 6.2% |
| Worcester ($K/MWi) | 324 | 315 | 343 | 286 | 295 | 340 |
| $\Delta$ | | -2.9% | 5.8% | -11.7% | -8.9% | 5.0% |
| **Demand** | | | | | | |
| Total (M MWH) | 488 | 477 | 471 | 483 | 481 | 472 |
| $\Delta$ | | -2.4% | -3.5% | -1.2% | -1.6% | -3.4% |
| **Emissions** | | | | | | |
| $CO_2$ (B kg) | 613 | 600 | 593 | 607 | 605 | 594 |
| $\Delta$ | | -2.2% | -3.3% | -1.0% | -1.4% | -3.1% |
| $SO_2$ (M kg) | 858 | 840 | 831 | 850 | 847 | 832 |
| $\Delta$ | | -2.1% | -3.2% | -1.0% | -1.3% | -3.0% |
| $NO_x$ (M kg) | 389 | 377 | 373 | 382 | 381 | 374 |
| $\Delta$ | | -2.9% | -4.0% | -1.7% | -2.0% | -4.0% |

## C.4 Partial Adoption of RTP

The literature surveyed in Chapter Three showed that welfare benefits are expected even with a fraction of customers on RTP. In this section I will show how the model in Chapter Four would be modified to allow a fraction of consumers to remain on the flat tariff. The objective is to show that this modification would not qualitatively alter my results regarding renewable generators or emissions.

In a certain hour, we start with observed demand and retail price, $Q_{obs}$ and $P_{obs}$. In the counterfactual scenario, the fraction $\alpha$ of consumers will face RTP. This segment's aggregate demand at price $P_{obs}$ is therefore $\alpha * Q_{obs}$, and the flat-tariff segment's demand is $(1-\alpha)Q_{obs}$. Now that some consumers face RTP, their demand schedules are defined by

$$Q_{flatsegment} = (1-\alpha)Q_{obs} \tag{C.1}$$

for each flat-tariff customer and

$$Q_{RTPsegment} = \alpha * A * P_t^{\epsilon} = \alpha \frac{Q_{obs}}{P_{obs}^{\epsilon}} P_t^{\epsilon} \tag{C.2}$$

so the aggregate demand is

$$Q = (1-\alpha)Q_{obs} + \alpha \frac{Q_{obs}}{P_{obs}^{\epsilon}} P_t^{\epsilon} \tag{C.3}$$

The aggregate demand schedule is plotted for four values of $\alpha$ with all else equal in Figure C-3. This figure is intended to show that the effect of retaining a fraction of consumers on flat tariff simply reduces the effective elasticity at all prices (although the elasticity is no longer constant), i.e. the slope is increased at all values of $Q$. Since the results presented in Chapters Five and Six are not qualitatively sensitive to the elasticity (although the magnitude of response is), I expect these results to be similarly insensitive to scenarios with less than 100% of consumers on RTP. Just as with lower elasticities, as the fraction remaining on the flat tariff approaches 100%, the effect of RTP on all generators will be attenuated, but the intermittent generators examined in Chapter Five should continue to lose less than the sector as a whole at any given level[2].

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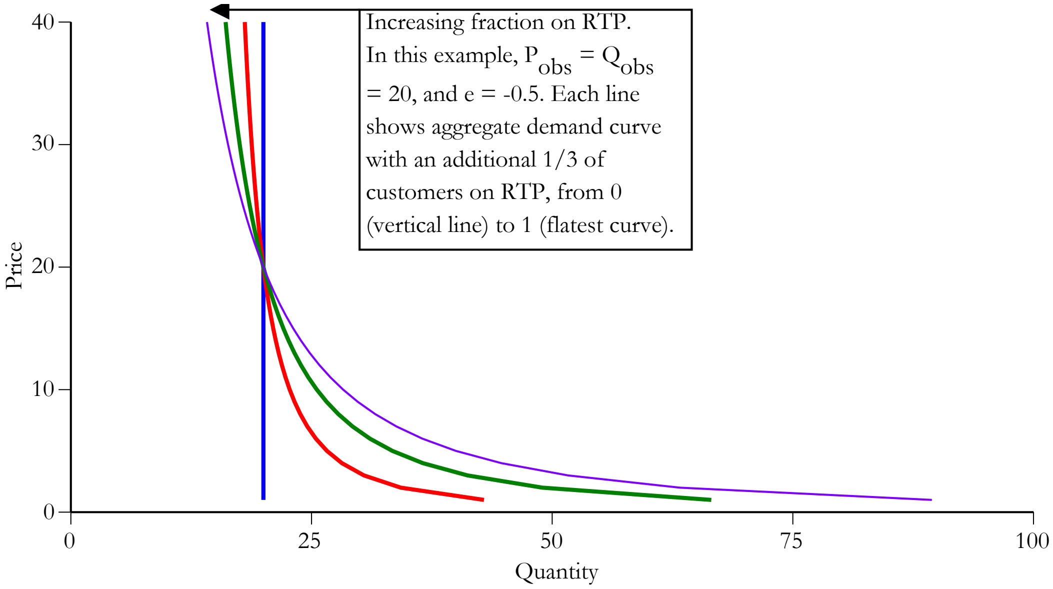
[2] Note that this analysis assumes that the flat retail price is not changed by the introduction of RTP. In

Figure C-3: Aggregate Demand Schedule with Fraction of Consumers Remaining on Flat Tariff



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reality, RTP may lower flat prices by lowering the cost of serving all customers averaged over time. A change in the flat retail price is equivalent to a shift in the flat-tariff customer's demand curve (lower prices induce an outward shift), which translates to a shift in the aggregate demand curve. Since I show in the first section of this chapter that my results are qualitatively insensitive to shifts in demand, I expect that an inclusion of this subtlety in the discussion above would not change the substantive results.